Universität Zürich[UZH]

Am I There Yet? A Motivational Life-Span Approach to Exhaustion and Recovery

Thesis (cumulative thesis)

presented to the Faculty of Arts and Social Sciences

of the University of Zurich

for the degree of Doctor of Philosophy

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Accepted in the spring semester 2019

on the recommendation of the doctoral committee:

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Zurich, 2019

ABSTRACT

This thesis is guided by the overarching question of how people determine when they are exhausted or when they have recovered. Taking a motivational approach, it defines exhaustion and recovery as motivational states that prompt disengagement from an ongoing activity that has begun to net more costs than benefits. To this end, the thesis introduces perceived changes in mood, in opportunity costs, and in subjective time perception as psychological indicators of exhaustion and recovery. Taking a life-span approach, it further proposes age-differential effects of opportunity costs and subjective time perception on exhaustion and recovery (Part I). These propositions were tested in a set of methodologically diverse studies encompassing micro-longitudinal laboratory experiments (Parts II and III), a longer-term daily diary study in a naturalistic recovery setting (Part IV), and large online surveys that complement the main studies (Parts II, III, and V). Taken together, this thesis yielded the following main results: (1) Good mood is positively related to recovery; bad mood is positively related to exhaustion. (2) Opportunity costs are unrelated to recovery and are positively related to exhaustion. (3) A subjective acceleration of the passage of time is unrelated to recovery; a subjective extension of the passage of time is positively related to exhaustion. (4) Older adults, as compared to younger adults, report faster initial increases in opportunity costs and exhaustion during an exhaustion period. (5) Older adults, as compared to younger adults, do not differ in their subjective recovery during a subsequent recovery period. The theoretical, methodological, and practical implications of these findings are elaborated on in the Overall Discussion.

ZUSAMMENFASSUNG

Die vorliegende Dissertation beschäftigt sich mit der Frage, wie Menschen erkennen, wann sie erschöpft bzw. erholt sind. Dabei werden Erschöpfung und Erholung definiert als motivationale Zustände, die die Ablösung von einer Aktivität begünstigen, die begonnen hat, mehr Kosten als Nutzen einzubringen. In diesem Rahmen führt die vorliegende Dissertation wahrgenommene Veränderungen in der Stimmung, in den Gelegenheitskosten und in der subjektiven Zeitwahrnehmung als psychologische Kennzeichen der Erschöpfung und Erholung ein. Ferner werden altersunterschiedliche Einflüsse der Gelegenheitskosten und der subjektiven Zeitwahrnehmung auf die Erschöpfung und Erholung vorgeschlagen (Teil I). Diese Propositionen wurden in einer Reihe von methodologisch diversen Studien getestet, bestehend aus mikro-längsschnittlichen Laborexperimenten (Teile II und III), einer länger andauernden Tagebuch-Feldstudie in einem natürlichen Erholungsumfeld (Teil IV) und umfassenden Online-Studien, die die Hauptstudien ergänzen (Teile II, III und V). Zusammenfassend haben sich folgende Hauptresultate ergeben: (1) Gute Stimmung hängt positiv mit der Erholung zusammen; schlechte Stimmung hängt positiv mit der Erschöpfung zusammen. (2) Gelegenheitskosten hängen nicht mit der Erholung zusammen und hängen positiv mit der Erschöpfung zusammen. (3) Eine Beschleunigung des subjektiven Zeitempfindens hängt nicht mit der Erholung zusammen; eine Ausdehnung des subjektiven Zeitempfindens hängt positiv mit der Erschöpfung zusammen. (4) Ältere Erwachsene, verglichen mit jüngeren Erwachsenen, berichten über einen schnelleren anfänglichen Anstieg der Gelegenheitskosten und der Erschöpfung in einer Erschöpfungsphase. (5) Ältere Erwachsene, verglichen mit jüngeren Erwachsenen, unterscheiden sich nicht in ihrer wahrgenommenen Erholung in einer anschliessenden Erholungsphase. Die theoretischen, methodologischen und praktischen Implikationen dieser Befunde werden in der anschliessenden Diskussion erörtert.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deepest gratitude to Prof. Dr. Alexandra M. Freund, who has expertly and tenaciously advised me during my academic "coming-of-age" journey. Without her keen insight, sage advice, and contagious work ethic, this project would never have come to fruition—and I would probably still pride myself as a "cognitive miser." Simply put, she has taught me the courage to try and live up to my full potential rather than settle for the safe bounds of mediocrity, and for this I am forever grateful to her.

I would also like to sincerely thank Prof. Dr. Michaela Riediger for reading my research proposal at the beginning stages of this project, for our productive meeting at the MPI in Berlin, and for agreeing to be a member of my dissertation committee. Her comments have always been to the point and proved very helpful in getting this project off the ground.

Furthermore, I would like to express my warmest appreciation to all the members of the Life-Management Lab—current and past—who have been (and continue to be) wonderful constants on this journey. I have crossed paths with simply too many great people to list them all here exhaustively. Nevertheless, I would like to individually thank Dr. Oliver Kaftan, for being an incredibly caring and attentive colleague; Lea Mörsdorf, for the engaging conversations that need not always revolve around work; Zita Mayer, whose sharp—and frankly terrific—intellect kept me on my toes; Isabel Hotz, for her energizing sociality; and Dr. Michaela Knecht, for her kind support during the conceptual stages of this project.

My employment at the University of Zurich was funded by the University Research Priority Program (URPP) "Dynamics of Healthy Aging." To this end, I would like to sincerely thank all the Directors of the URPP and, most notably, Dr. Christina Röcke, for her support throughout the years and for agreeing to be a member of my dissertation committee. I would also like to extend my thanks to all the pre- and postdocs of the URPP who took time out of their busy schedules to attend my talks in the research colloquia.

I have benefited tremendously from presenting my work-in-progress at the Academies of the International Max Planck Research School on the Life Course (LIFE) and from the fruitful onsite discussions with fellows and faculty alike. I am especially thankful to Prof. Dr. Gerald Clore and Prof. Dr. Cindy Lustig, for reading my dissertation proposal and giving detailed feedback; to Prof. Dr. Michael Kubovy, for the insightful meetings that always provided a different viewpoint on a particular topic of interest; and to Prof. Dr. Steven Boker and Prof. Dr. Michael Eid, for sharing their vast methodological expertise with me.

Working in a high stress environment necessitates appropriate balance in the form of relieving leisure. I count myself very lucky to have had Jasmin Bernath steadfastly accompany me through the good times and the bad. I am also indebted to all my friends and family, above all my parents, Carmen and Olivier; my brother, Steven; and my sister-in-law, Halina; for being there in times of need—but also in the far more numerous moments of peace and merriment.

Last but not least, I would like to thank Lisa Makowski, Oliver Kälin, Ebru Yetik, Joel Siebenmann, and Julia Wolf for their sheer endlessly enthusiastic support in running the demanding exercise studies, and to the many students and community dwellers who were willing to participate in the present research. Without all their help, this thesis would not have been possible.

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INTRODUCTION

> How is it that we can feel tired when we do not appear to have done very much? How is it that we appear to be able to recover so quickly under some conditions, but not others? What is going on when weariness following a hard day at work can be banished by going for a run or a session at the gym? Why do some kinds of activity make us feel tired, while others, equally or even more demanding, do not? (Hockey, 2013, p. 1)

In these introductory remarks for his comprehensive monograph on exhaustion, Robert Hockey has aptly paved the way for the present thesis. Indeed, the rationale for the present thesis was born out of a series of related anecdotal peculiarities: Why is it that, given the possibility, we do not engage in recovery activities indefinitely? Why do we sometimes take pleasure in exhausting ourselves instead? And most importantly: How do we know when we are exhausted or when we have recovered? What is happening when we decide to stop browsing the internet and to resume work, or when we seemingly have no other choice but to interrupt an ongoing sprint to catch our breaths? In an attempt to answer these questions, the present thesis examines *psychological indicators* of exhaustion and recovery (i.e., perceived internal changes that are taken as information about one's current extent of exhaustion or recovery and impact one's decision to disengage from an ongoing activity).

Before delving into the main theoretical part of this thesis that provides a comprehensive conceptualization of exhaustion and recovery and a detailed introduction to their proposed psychological indicators, it is necessary to first highlight some general challenges pertaining to the study of exhaustion and recovery, and how the present thesis addresses them. More specifically, in the following two sections I discuss prominent approaches toward measuring and inducing exhaustion and recovery in experimental settings and highlight their pertinent limitations. Based on these considerations, I then make the case for taking a psychological approach to exhaustion and recovery and for inducing exhaustion and the need for recovery through effortful physical exercise.

Challenges in the Measurement of Exhaustion and Recovery

How to best measure exhaustion and recovery in experimental settings? A long-standing research tradition has focused on decrements in *task performance* (e.g., decreasing accuracy and increasing reaction time) as a characteristic and observable expression of exhaustion (Ackerman, 2011; Bartley & Chute, 1947; Boksem & Tops, 2008; Hockey, 2013; Thorndike, 1914). The central assumption underlying this approach is that as time-on-task increases, so does exhaustion, which in turn reduces participants' ability to maintain the level of performance required to succeed at the task. Indeed, a particularly influential application of this approach – the sequential-task paradigm – has been used to validate classical work related to exhaustion and recovery, such as the strength model of self-control (Muraven & Baumeister, 2000) and attention restoration theory (Kaplan, 1995).

This approach is problematic for at least two reasons. First, task performance is strongly linked to *motivation*, such that participants are more likely to spend effort and perform well on a demanding task when they perceive a sufficiently high likelihood of succeeding as well as sufficiently high intrinsic and/or extrinsic incentives (Brehm & Self, 1989; Richter, Gendolla, & Wright, 2016). Experimental settings that do not clearly disentangle the processes underlying changes in task performance cannot, therefore, make strong inferences as to why performance declines or increases in the first place (Muscio, 1921; Navon, 1984). Second, there is well-documented variability in the *direction* of change in task performance in the presence of subjective exhaustion, with some studies reporting stability or even an increase in performance in exhausted participants (Ackerman, 2011; Ackerman & Kanfer, 2009; van Cutsem et al., 2017). It seems that exhausted participants can still be motivated to exert compensatory effort on a demanding task in an attempt to maintain high levels of performance. Based on these considerations, task performance seems ill-suited as a “be-all and end-all” proxy variable for exhaustion and recovery.

Should experimental settings instead rely on other objective markers of exhaustion and recovery, such as physiological correlates? On the one hand, a considerable amount of research has linked changes in physiological indicators such as heart rate variability (Luft, Takase, & Darby, 2009; Segerstrom & Nes, 2007), body temperature (Nybo, 2008), oxygen uptake (Ament & Verkerke, 2009), oxidative stress (Finaud, Lac, & Filaire, 2006), and blood lactate concentration (Jacobs, 1986) to exhaustion and recovery periods. On the other hand, “it is not possible to measure more easily observable aspects of emotion (e.g., facial movements, vocal acoustics, voluntary behaviors, *peripheral physiology* [emphasis added]) to learn something about its subjective aspect” (Barrett, Mesquita, Ochsner, & Gross, 2007, p. 376). Indeed, studies have shown that changes in peripheral physiology during exhaustion and recovery periods are *unrelated* to the accompanying subjective experience (Bartley & Chute, 1947; Marcora, 2009; Marcora, Staiano, & Manning, 2009; Smirmaul, 2012; van Cutsem et al., 2017; but see Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005). For instance, in his literature review on the relation between physiology and subjective effort, Marcora (2009, p. 2061) concluded that, “although essential for a variety of other physiological and perceptual processes such as cardiorespiratory regulation and sense of position and movement, afferent feedback from skeletal muscles, heart, and lungs does not contribute significantly to perception of effort during exercise.” Taken together, this research suggests that there is no clear relationship between peripheral physiology and subjective experiences related to exhaustion and recovery.

Absent more compelling and valid behavioral and objective measures, it seems reasonable to take a psychological perspective on exhaustion and recovery. Speaking for the psychological perspective, Staiano, Bosio, de Morree, Rampinini, and Marcora (2018) demonstrated in two experiments that perception of effort, rather than muscle fatigue or muscle pain, was the best predictor of exhaustion-related exercise termination during high-intensity aerobic exercise. Furthermore, Giles et al. (2018) found that the way people regulate their emotions during physical exercise impacts how effortful they perceive the activity to be. In a more general sense, Knecht and Freund (2015) found that people categorize everyday life activities involving physical effort as exhausting and relaxing similarly often. This finding is corroborated in a study by Rook and Zijlstra (2006), who found that some people perceive physical activity as a remedy from stressful work demands. Taken together, this research suggests that what determines an activity as exhausting or relaxing is not primarily determined by its objective properties but rather by how a person perceives it. Thus, taking a psychological perspective on exhaustion and recovery (i.e., assessment through self-report) provides a valid method to studying the subjective experience underlying these constructs.

Challenges in the Induction of Exhaustion and Recovery

Having established a reasonable approach toward measuring exhaustion and recovery, the question arises: How to best induce these states in experimental settings? Perhaps the most common way of inducing exhaustion in the lab is to have participants solve a series of repetitive and/or mentally demanding tasks for a prolonged period of time (for a detailed overview, see Ackerman, 2011). As such, a considerable amount of research has focused on tasks targeting different facets of executive functioning, such as *attentional vigilance* (e.g., monitoring displays for low frequency targets in high frequency noise; Boksem, Meijman, & Lorist, 2005; Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2011), *working memory* (e.g., deciding whether each stimulus in a sequence matches the one that appeared a specified number of items ago; Hopstaken, van der Linden, Bakker, & Kompier, 2015; Owen, McMillan, Laird, & Bullmore, 2005), and *inhibition* (e.g., identifying the print color of a target color word that spells a different color; Pageaux, Marcora, Rozand, & Lepers, 2015; Wright, Stewart, & Barnett, 2008).

These approaches are problematic for at least three reasons. First, the mental tasks are typically administered for two to five hours without rest to produce task performance decrements and induce subjective exhaustion (e.g., Ackerman & Kanfer, 2009; Gergelyfi, Jacob, Olivier, & Zénon, 2015). Such a time-intensive procedure drastically reduces the test efficiency of these tasks and increases respondent burden, which might in turn lead to underpowered study designs due to insufficient sample sizes (e.g., Boksem, Meijman, & Lorist, 2006). Second, with increasing time-on-task it becomes more difficult to distinguish exhaustion from various other negative affective experiences, such as boredom and frustration (Milyavskaya, Inzlicht, Johnson, & Larson, 2019; Pattyn, Neyt, Henderickx, & Soetens, 2008). Third, the accumulated subjective exhaustion during a mentally demanding task might not transfer to subsequent tasks (Hagger et al., 2016; Hopstaken et al., 2015), thus making it difficult to study the temporal dynamics of recovery from exhaustion.

A potential solution consists of having participants engage in effortful *physical* activity instead. As mentioned previously, the subjective sense of effort during physical exercise has been singled out as the best predictor of exhaustion-related disengagement from exercise (Marcora et al., 2009; Staiano et al., 2018). Furthermore, engaging in physical activity can become taxing very quickly, depending on the extent of exertion. For instance, running up and down the stairs of a 5-floor building as quickly as possible is likely to result in a pronounced state of exhaustion in a matter of minutes. Finally, physical exertion necessitates a subsequent recovery period due to biological constraints (Kellmann, 2002) – a notion that does not seem to apply to short-term mental exertion (Inzlicht, Schmeichel, & Macrae, 2014). For these reasons, the present thesis employs demanding physical activity as a means to induce exhaustion and establish a subsequent need for recovery.

The Current Work

The overarching aim of this thesis is to theoretically introduce (Part I) and empirically examine (Parts II-V) the role of *perceived opportunity costs* (i.e., the experienced costs of forgoing the next-best alternative activity compared to the benefits of staying engaged in the focal activity; Kurzban, Duckworth, Kable, & Myers, 2013), *mood*, and *subjective time perception* as psychological indicators of exhaustion and recovery under the lens of a dynamical and motivational life-span perspective. In doing so, the present thesis answers the call to shed light “on the dynamics of recovery from fatigue” (Hockey, 2013, p. 205) and on how “the effectiveness of specific recovery activities or experiences change[s] with age” (Sonnentag, Venz, & Casper, 2017, p. 373). In this section, I briefly highlight the conceptual and methodological advances put forward by the present thesis before giving an overview of the main theoretical and empirical parts that are to follow.

Conceptually, the current thesis advances previous work in four important ways. First, it proposes a unifying account of exhaustion and recovery that jointly integrates both constructs and illuminates their experiential components and short-term motivational consequences (Evans, Boggero, & Segerstrom, 2016). Second, it describes a potential metacognitive mechanism that might explain when people begin to feel exhausted or recovered through the weighing of subjective costs and benefits of the current environment (Hockey, 2013; Inzlicht et al., 2014; Kool & Botvinick, 2014; Kurzban et al., 2013). Third, it emphasizes the dynamic nature of exhaustion and recovery and their psychological indicators during an ongoing activity, thereby moving beyond restrictive pre-post designs (Ackerman, 2011). Fourth, it generates and tests hypotheses about age-differential effects of exhaustion, recovery, and their psychological indicators – an as yet neglected research avenue (Sonnentag et al., 2017).

Methodologically, the current thesis advances previous work by focusing its scope of analysis on the estimation of interindividual differences in intraindividual variability (Molenaar & Campbell, 2009; Nesselroade, 1991; Nesselroade & Ram, 2004; Röcke & Brose, 2013). As such, a central methodological focus of this thesis lies on univariate and multivariate multilevel growth curve modeling (Bliese, 2000; McArdle & Nesselroade, 2003), using both frequentist and Bayesian inference (Bürkner, 2017). More specifically, the focus of analysis lies on the estimation of cross-level main effects and interactions (Mathieu, Aguinis, Culpepper, & Chen, 2012) and correlated within-person change between two variables over time (Hertzog, Lindenberger, Ghisletta, & von Oertzen, 2006; MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997). Taking such a dynamic approach allows for a more fine-grained examination of the temporal patterns of exhaustion, recovery, and their proposed indicators, both at the within- and between-person level.

Part I: When the Fun is Over: Toward a Motivational Account of Exhaustion and Recovery

Part I provides a comprehensive theoretical introduction to the research reported in this thesis. Here, we tackle the challenging task (cf. Bartley & Chute, 1947; Hockey, 2013) of properly defining the concepts of exhaustion and recovery by integrating different strands of literature and distinguishing both concepts from similar constructs, such as boredom, interest, and mood. Furthermore, we review past theoretical and empirical research on influential limited resource models of exhaustion and recovery (Ryan & Deci, 2008; Kaplan, 1995; Kaplan & Berman, 2010; Muraven & Baumeister, 2000) and point out their conceptual (Navon, 1984), methodological (Friese, Loschelder, Gieseler, Frankenbach, & Inzlicht, 2018; Wright, Mlynski, & Carbajal, 2019), and empirical (Carter, Kofler, Forster, & McCullough, 2015) limitations. As a result, we align ourselves with research advocating for taking a motivational approach to understanding exhaustion and recovery (Hockey, 2013; Inzlicht et al., 2014; Kool & Botvinick, 2014; Kurzban et al., 2013). Building on this motivational framework, we introduce the notion of perceived opportunity costs (Kurzban et al., 2013), mood (Clore & Huntsinger, 2007), and subjective time perception (Zakay, 2014) as psychological indicators of exhaustion and recovery. Next, we integrate this theoretical background into a novel motivational account of exhaustion and recovery. In short, we propose that perceiving an increase in opportunity costs, a decline in positive mood, and an extension of the felt pace of time is taken as an indication that one is exhausted or has recovered, depending on the motivational context, and should therefore disengage from the focal activity. Lastly, we review literature on age-related differences in the role of opportunity costs, mood, and subjective time perception for exhaustion and recovery.

Part II: The Role of Mood and Opportunity Costs for Subjective Recovery

Part II presents four methodologically diverse studies testing the hypothesis that perceived opportunity costs, mood, and subjective time perception are related to subjective recovery from exhaustion. Study 1 is a large online study that examines people's lay beliefs about what thoughts, feelings, and behaviors indicate to them exhaustion and recovery in their everyday lives using a content analysis approach. Studies 2-4 are laboratory experiments with the aim to induce a state of exhaustion through demanding physical activity (Study 2: 20-minute high-intensity interval training; Studies 3 and 4: 5-minute stair running). In these studies, the focus of analysis lies mostly on the subsequent relaxing activity (watching a 25-minute excerpt of an aquatic documentary), where we investigate the correlated change in perceived opportunity costs, mood, as well as subjective time perception and subjective recovery using a micro-longitudinal design (Studies 2 and 3: 10 measurement occasions; Study 4: eight measurement occasions). Furthermore, Studies 3 and 4 develop a between-person manipulation of perceived opportunity costs and test its effect on the subjective speed of recovery during the relaxing activity.

Part III: More or Less Energy with Age? A Motivational Life-Span Perspective on Energy, Exhaustion, and Opportunity Costs

Part III takes a lifespan-developmental approach to exhaustion and recovery. Study 1 is a comprehensive online study that investigates people's lay beliefs about the limitedness of their energy as a means for goal pursuit, the availability of energy for goal pursuits related to different functional domains (i.e., physical, mental, social, emotional), as well as within- and cross-domain energy spillover effects (e.g., the extent to which spending energy on a demanding physical activity affects one's perceived available energy for mental activities). Study 2 aims to replicate part of the findings and extend the methodology of Part II by investigating (1) between- and within-person variability in subjective exhaustion and recovery, perceived opportunity costs, mood, and subjective time perception during both a demanding physical activity (20-minute high-intensity interval training; 11 measurement occasions) and a subsequent relaxing activity (20-minute mindfulness-based relaxation video; 10 measurement occasions), and (2) age-related differences in this within-person variability.

Part IV: How to Recharge During a Vacation: The Role of Daily Mood and Opportunity Costs for Recovery

Part IV complements Parts II and III by examining the role of perceived opportunity costs, mood, and subjective time perception for recovery from exhaustion on a different time scale: the day level. Using a daily diary design over 21 consecutive days in a naturalistic recovery setting (i.e., student's summer break from a demanding exam period), here we investigate the predictive validity of within- and between-person variability in daily opportunity costs, mood, and subjective time perception for explaining variability in daily recovery, over and above well-established factors contributing to daily recovery (i.e., daily psychological detachment, relaxation, mastery, and control; Sonnentag & Fritz, 2007).

Part V: Development and Initial Validation of a General Exhaustion and Recovery Scale

Part V chronicles the development and initial validation of a scale that measures exhaustion and recovery as separate factors and can be applied at the trait and state level. Study 1 summarizes the item generation process. Study 2 examines the factorial structure of the selected exhaustion and recovery items using exploratory factor analysis. Study 3 cross-validates the factorial structure of the scale using confirmatory factor analysis on a new data set. Finally, Study 4 investigates the sensitivity of the scale in detecting changes in state exhaustion and recovery following a series of effortful mental tasks, as well as the convergent and discriminant validity of the scale. Notably, Study 4 also includes a between-person manipulation of retrospective time perception following the mentally demanding tasks and examines its effect on exhaustion and recovery.

PART I: WHEN THE FUN IS OVER: TOWARD A MOTIVATIONAL ACCOUNT OF EXHAUSTION AND RECOVERY

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This article is published (2019) in *European Psychologist*. Advance online publication. https://doi.org/10.1027/1016-9040/a000361.

Abstract

How do we know when an activity has exhausted us or helped us recover? In this paper, we present a motivational approach to exhaustion and recovery that takes into account the multidimensional nature of the constructs. The account details three psychological processes that may – individually and in interaction – underlie exhaustion and recovery. Specifically, we propose that changes in mood, subjective time perception, and opportunity costs experienced during an ongoing effortful or relaxing activity indicate a person's momentary degree of exhaustion and recovery and impact the decision of whether the person should continue or disengage from the activity at hand. Addressing developmental changes across adulthood, we present two opposing hypotheses on how younger and older adults may differ in their experiences of exhaustion and recovery: (i) Older adults may experience an accelerated subjective time perception compared to younger adults, and may thus feel less exhausted (more recovered) than younger adults after spending an identical amount of time engaged in an effortful (relaxing) activity. (ii) Older adults may be more sensitive towards increasing opportunity costs experienced during an effortful or relaxing activity and may therefore feel exhausted or recovered faster than younger adults.

Introduction

Picture the following scenario: Tom has been working hard on digging up the garden for quite some time and wants to proceed for as long as he can. Thirty minutes later, he has to call it quits: Tom is in a bad mood, time seems to drag, and thoughts on all the things he would rather do instead become more and more intrusive. Thus, Tom decides to watch some episodes of his favorite TV show. For quite some time, he greatly enjoys watching the show. Tom’s mood gets better. He sporadically checks his watch and is surprised to see how quickly time has passed. Two and a half episodes later, however, Tom’s mood starts to worsen and his enjoyment to wane. He checks his watch more frequently now, wondering why these latest scenes seem so boring. Shortly thereafter, Tom turns off the show and resumes digging up the garden.

How did Tom know when it was time for him to disengage from garden work or watching TV? More specifically, what psychological processes might have indicated to Tom that he was exhausted and sufficiently recovered? This is the central topic of this paper. Drawing on the affect-as-information approach (Clore & Huntsinger, 2007; Clore, Wyer, Dienes, Gasper, & Isbell, 2001), the literature on subjective time perception (Wearden, 2015; Zakay, 2014), and opportunity cost models of subjective effort (Hennecke & Freund, 2013; Kurzban et al., 2013), we propose that changes in mood, subjective time perception, and opportunity costs experienced during an effortful or relaxing activity indicate to a person that the currently pursued activity has fulfilled its recovery function or has become too exhausting to continue.

Using the scenario of Tom, we posit that with increasing exhaustion stemming from the garden work, Tom’s mood worsens, he perceives time as passing more slowly, and opportunity costs as increasing. In contrast, the recovery induced by watching TV should gradually restore Tom’s mood, accelerate his subjective time perception, and should not evoke any opportunity costs for as long as the experience is helping Tom unwind. However, once Tom has sufficiently recovered, we maintain that these psychological processes start to change *again*; that is, his mood should begin to decline, time perception to extend, and opportunity costs to become salient. In our approach, these internal changes are adaptive responses indicating to Tom that it is time to disengage from the current activity and do something else instead, to avoid remaining engaged in an activity that does no longer yield positive results, such as becoming ineffective in digging up the garden or wasting valuable time by watching too much TV.

The aim of this paper is to introduce a motivational and functional approach to exhaustion and recovery as signaling goal disengagement. Despite the ubiquity of experiencing exhaustion and recovery, only little is known about the psychological indicators that inform us when an activity has exhausted or recovered us. For instance, given the opportunity, why do we not engage in pleasant and relaxing activities indefinitely? What prevents us from investing resources such as time or effort into an activity that is – temporarily – no longer contributing significantly to further goal achievement? We posit that exhaustion signals that the "return of investments" has fallen under that of the next best alternative. Similarly, feeling sufficiently recovered signals, in our view, that time and effort are better spent on another activity.

In this paper, we first review and discuss the extant literature on exhaustion and recovery. Then, we conceptualize opportunity costs, mood, and subjective time perception as psychological indicators of exhaustion and recovery. Next, we integrate the theoretical background presented in this paper into a functional and motivational account of exhaustion and recovery. Lastly, we discuss how exhaustion and recovery and their indicators may change across adulthood.

Conceptualizing Exhaustion and Recovery

Exhaustion

Psychologists often use the term exhaustion interchangeably with fatigue (e.g., Féry, Ferry, Vom Hofe, & Rieu, 1997), referring to a multidimensional construct comprising physical, cognitive, and emotional components (e.g., Maslach & Jackson, 1981). For example, Smets, Garssen, Bonke, and De Haes (1995, p. 315) define exhaustion as “a normal, everyday experience that most individuals report after inadequate sleep or rest, or after exertion of physical power,” adding that cognitive effort can also contribute to exhaustion. More often, researchers conceptualize exhaustion with regard to a specific functional domain. For example, Boksem and Tops (2008) define *cognitive exhaustion* as the feeling during or after a prolonged period of cognitive activity encompassing tiredness, an aversion to continue the current activity, and a decrease in commitment to the activity at hand. Wright and Cropanzano (1997, p. 486) conceptualize *emotional exhaustion* as “a chronic state of physical and emotional depletion that results from excessive job demands and continuous hassles.” Interestingly, this latter definition of emotional exhaustion also includes physical depletion. This implies that the different functional domains in which exhaustion occurs may be closely related. Note also, that Wright and Cropanzano view emotional exhaustion as a consequence of work demands rather than of an emotionally demanding event (e.g., an argument with a close friend), further suggesting that the functional domains might be interrelated. This raises the question of how effortful or relaxing activities in one functional domain (e.g., physical exercise) affect the state of recovery or exhaustion in a different functional domain (e.g., cognition, motivation). There is some evidence about cross-domain influences: Marcora et al. (2009) have shown that cognitive exhaustion can have a negative impact on subsequent physical performance. Conversely, Brisswalter, Collardeau, and René (2002) demonstrated that physical exercise can prove beneficial for subsequent cognitive performance.

Taken together, exhaustion seems to be associated with changes in physical (e.g., increased tiredness and low energy), cognitive (e.g., increased aversion to the current activity), emotional (e.g., negative mood), but also motivational (e.g., reduced commitment to the activity at hand) and behavioral (e.g., reduced activity performance) processes. Some of these characteristics also pertain to the phenomenon of boredom. Bored people also perceive their current activities as unpleasant and uninteresting, and show an increased motivation to disengage from them (van Tilburg & Igou, 2012). To distinguish boredom from other negative states including exhaustion, van Tilburg and Igou (2012) have argued that boredom is associated with feeling unchallenged by the current situation and perceiving current activities as meaningless. Thus, in their view, the dimensions “challenge” and “meaning” distinguish the state of boredom from exhaustion. However, recent research has shown that, similar to exhaustion, boredom can also result from feeling over-challenged, when such a state leads to problems in maintaining attention (Milyavskaya et al., 2019; Raffaelli, Mills, & Christoff, 2017). Thus, we argue that it is primarily the “meaning” dimension that distinguishes boredom from exhaustion (van Tilburg & Igou, 2017). What makes an activity meaningful is determined by the interaction of the value of the outcome of the activity and the instrumentality of the activity to achieve it (van Tilburg & Igou, 2013). Thus, when an activity (e.g., reading a theoretical paper) is perceived as effortful yet not instrumental (e.g., the paper is deemed uninformative) to the associated outcome (e.g., gaining more insight into a particular branch of psychological research), that, in addition, is of little personal value, then this activity is more likely to induce boredom rather than exhaustion.

Recovery

The concept of recovery has been examined from various angles in different fields of psychology. Even within one research area, the term is often only vaguely defined and may refer to different aspects of recovery. For instance, clinical psychologists define recovery

very broadly as a process of changing from displaying abnormal patterns of behavior to showing more normalized patterns of behavior (e.g., Leamy, Bird, Le Boutillier, Williams, & Slade, 2011). Sports psychologists refer to recovery as the resting and relaxation period that is preceded by an interval of physical effort (e.g., Kellmann, 2002). Environmental psychologists use the terms restoration and recovery interchangeably and emphasize the role of natural environments for recovery (Kaplan, 1995). Occupational health psychologists see recovery as a dynamic process that restores a person's energetic and cognitive resources following stressful work demands (Zijlstra, Cropley, & Rydstedt, 2014).

Before providing our own definition of recovery, it is important to conceptually distinguish recovery from other positive affective states such as relaxation, interest, relief, and happiness. First, *relaxation* mainly refers to the down-regulation of physiological arousal (Benson, 1975) that can be achieved by various techniques such as mindfulness (Brown, Ryan, & Creswell, 2007) and progressive muscle relaxation (Esch, Fricchione, & Stefano, 2003). By this definition, achieving relaxation precludes engaging in any form of physical activity. In contrast, research has shown that physical activity can lead to states of recovery (e.g., Sonnentag & Zijlstra, 2006). Thus, we posit that relaxation is a sufficient, but not a necessary condition for recovery. Second, *interest* is a narrow construct that emerges when an activity or event is perceived as new, complex, unexpected, and comprehensible (Silvia, 2008). In comparison, recovering activities need not necessarily fulfill these criteria. For instance, listening to music is a pleasant and relaxing activity (e.g., Thayer, Newman, & McClain, 1994) and often encompasses listening to one's favorite songs that are well known (and hence do no longer offer surprises). Third, *relief* is "an emotion that is experienced in situations in which (a) the actual outcome of a course of action is positive or neutral and (b) a possible alternative decision would have resulted in a more negative outcome (Guttentag & Ferrell, 2004, p. 764). In order to experience relief, a person needs to actively compare the actual with a potential negative outcome, and this comparison needs to favor the actual outcome. There is no reason to assume that recovery involves such a comparison that requires the representation of a counterfactual negative state. Fourth, *happiness* is a broad construct encompassing affective (i.e., positively valenced moods and emotions) and cognitive (i.e., life satisfaction) components (Lyubomirsky, King, & Diener, 2005). Based on this definition, distinguishing happiness from recovery is difficult, especially when considering that some researchers view recovery as a process of "mood repair" (Sonnentag & Fritz, 2007). However, as we will elaborate in the following sections, we posit that happiness or positive mood is positively related to recovery only as long as a person has not achieved the goal of recovery. Once a person has achieved the goal of recovery, we propose that this person will start to feel less happy, indicating that the current activity should be discontinued. Thus, for reasons that will be outlined in the following sections, we maintain that recovery and happiness can be distinguished based on their differential time courses unfolding during the engagement in a relaxing activity.

Are Exhaustion and Recovery Emotions?

In much of the literature, emotions are defined as short, intensive states encompassing physiological, cognitive, and experiential processes that are aroused by specific events, objects, or people (e.g., anger, surprise) and elicit certain action tendencies (Russell, 2003). In contrast, moods are less specific states that vary along the dimension of valence (good – bad), are of longer duration, are not bound to a specific event, object, or people, and are not related to strong action tendencies but rather "color" our experiences, cognition, and behavior (e.g., Clore & Huntsinger, 2007; Parkinson, Totterdell, Briner, & Reynolds, 1996). According to this definition, recovery and exhaustion are moods rather than emotions.

According to psychological construction theories of emotion (e.g., Barrett, 2014), emotions are constructed events, not fixed, essential entities. When constructing an emotion, the brain combines multimodal sensory input (from the body and from the environment) with experience-based knowledge about emotions. As will be elaborated in detail below, we propose three psychological indicators of exhaustion and recovery – perceived changes in (i) opportunity costs, (ii) mood, and (iii) time perception during an effortful or relaxing activity. These indicators could be conceptualized as sensory inputs that convey information about the goodness or badness of an object (e.g., the current activity). In this view, exhaustion and recovery might qualify as emotional states.

However, based on the taxonomy of the affective lexicon proposed by Ortony, Clore, and Foss (1987), exhaustion and recovery do not seem like good candidates for emotions. Rather, the authors argue that "words such as 'exhausted,' 'sleepy,' and 'thirsty' refer more directly to Physical and Bodily states" (p. 351). The authors also note that such physical states can be accompanied by psychological aspects, such as changes in motivation or cognition, but they are not emotions.

Following the perspective of Ortony et al. (1987), we do not conceptualize exhaustion and recovery as emotions. First, we do not find it likely that exhaustion and recovery are always associated with a specific object. For instance, a person who feels exhausted at the end of a long day likely attributes his or her exhaustion to a number of events (e.g., work, time spent awake, physical activity, emotional arguments). Second, exhaustion and recovery can unfold over a longer period of time compared to specific emotional states such as fear or anger. Third, studies have found that the physiological responses that had been thought to be associated with exhaustion and recovery (e.g., heart rate variability) are actually unrelated to the phenomenology underlying the constructs (Marcora, 2009; Smirmaul, 2012). Taken together, exhaustion and recovery do not meet the commonly employed criteria for emotions. Instead, we conceptualize exhaustion and recovery as mainly motivational states that both prompt goal disengagement. We will build towards this conceptualization in the following sections.

Clarifying the Notion of Resources

The literature often refers to the depletion and restoration of resources as an important part of the exhaustion and recovery process (Zijlstra et al., 2014). However, researchers often fail to provide a definition of resources and their role for exhaustion and recovery. According to an influential definition by Hobfoll (2001), resources constitute a broad range of valued objects, personal characteristics, conditions, or energies if they help people in achieving desired outcomes. The list of resources outlined by Hobfoll includes positive emotional states, social status, or intelligence. Although these states are often related to better outcomes in a variety of situations, they seem to be generally desirable states rather than goal-relevant means that are invested into goal pursuit (Freund & Riediger, 2001). Navon (1984) would call such states “alterants,” which he contrasts with “commodities” that denote means that can be spent only once at any given point in time (e.g., money, time, effort). Distinguishing between alterants and commodities is particularly useful in the context of recovery and exhaustion because it distinguishes limited resources for goal pursuit (e.g., time, money, energy) and characteristics that may influence how these limited resources are used (e.g., moods, emotions, cognitions). In this perspective, recovery and exhaustion might affect both the subjective *availability* of limited resources, as well as the way we *use* them.

What is the role of resources for exhaustion and recovery? Do limited resources simply get “used up” when we engage in an exhausting activity and replenish when we recover (“my batteries are drained and need to recharge”)? Alternatively, exhaustion and recovery may be mainly motivational constructs and influence *how* we make use of limited resources. To approach this question, we must first understand what it means to be exhausted, the state that recovery aims to remedy. In the following two sections we provide an overview of the two most prominent theoretical approaches to exhaustion, limited resource models and cost-benefit models of exhaustion, and how they conceptualize the recovery process. We conclude these sections with the formulation of our own conceptualization of exhaustion and recovery.

Resource Depletion Models of Exhaustion

Why do effortful tasks seem to sometimes result in subsequent performance reductions and experiences of exhaustion? Limited resource models (e.g., Baumeister, Bratslavsky, Muraven, & Tice, 1998; Kaplan, 1995, 2001) state that voluntary and effortful cognitive activity, such as self-control or directed attention, depends on one or more depletable resources. According to these models, performance reductions and feelings of exhaustion are the direct result of resource depletion, and recovery denotes the process of restoring these depleted resources.

One influential limited resource model is the strength model of self-control (Baumeister et al., 1998; Baumeister, Vohs, & Tice, 2007; Muraven & Baumeister, 2000). The model maintains that all acts of self-control draw from a common and limited energy resource. Self-control describes a person’s capacity to resist impulses and temptations, and suppress the dominant response in a specific situation (Baumeister et al., 1998). The model predicts that exerting self-regulatory effort on a task drains this limited energy resource and leads to a state of self-regulatory failure, the so-called “ego depletion” effect. In this state, persons are likely to show reduced performance on a subsequent self-regulatory task (for a meta-analysis, see Hagger, Wood, Stiff, & Chatzisarantis, 2010). However, in recent years researchers have started to criticize the strength model of self-control (e.g., Carter & McCullough, 2013; Job, Dweck, & Walton, 2010). If a task involving self-regulation depletes some limited resource needed to succeed in that task, how can incentives (e.g., Boucher & Kofos, 2012; Capa, Bouquet, Dreher, & Dufour, 2013), positive affect (Tice, Baumeister, Shmueli, & Muraven,

2007) or interest (Thoman, Smith, & Silvia, 2011) counteract performance reductions in a subsequent self-regulation task? In fact, two recent meta-analyses have found that when publication bias is accounted for, the ego depletion effect may be no different than zero (Carter et al., 2015; Carter & McCullough, 2014). In addition, a recent pre-registered project encompassing 23 laboratories around the world failed to replicate the ego depletion effect (Hagger et al., 2016).

Another limited resource model is Kaplan's (1995, 2001) attention restoration theory. This model assumes that directed attention (i.e., a voluntary and effortful cognitive activity) is a limited resource and its depletion leaves a person cognitively exhausted. According to the theory, directed attention resources are best replenished when they are allowed to rest. Thus, the theory predicts that environments invoking the use of involuntary attention (i.e., an effortless activity) are best suited to replenish one's directed attention resources. Kaplan and Berman (2010) have proposed directed attention as the central depletable resource underlying all forms of self-regulation, information processing and executive functioning. However, while there is empirical evidence that people fare better on cognitive tasks after spending time in natural compared to urban environments (e.g., Kaplan & Berman, 2010), the conclusion that this performance-enhancing effect is due to a central resource having replenished more efficiently in natural than in urban environments is highly speculative: These studies do not demonstrate the existence of such a resource, let alone its depletion or restoration. Instead, researchers infer from task performance that the underlying cognitive system of interest behaves "as if" it were constrained by a limited resource. Navon (1984), writing about limited resource models in general, made a convincing argument that,

> The frequent cases in which the predictions do not bear out are dismissed by resorting to built-in escapes in the theory, such as, data limits, operation below full capacity,

> disparate resource composition, and so forth. This is probably the source of the self-reinforcing nature of the concept and the unfalsifiable status of the theory. (p. 231)

Taken together, limited resource models provide a relatively simple and intuitive framework of exhaustion and recovery as resource depletion and restoration processes. However, research has yet to provide convincing evidence that self-regulatory or attentional resources can be depleted and restored by providing quantifiable measures of these resources (instead of indirectly inferring them from performance measures that can be influenced by many factors other than resources).

Cost-Benefit Models of Exhaustion

Cost-benefit models of exhaustion assume that *motivation* plays a central role in determining a person's task performance and subjective feelings of exhaustion. These models posit that exhaustion primarily affects the way we allocate limited resources to the pursuit of multiple goals. Proponents of such models conceptualize exhaustion as an adaptive feeling that serves to maintain an effective overall management of one's goals (e.g., Boksem & Tops, 2008; Hockey, 2011; Inzlicht et al., 2014; Kool & Botvinick, 2014). For instance, Inzlicht et al. (2014) argue that feelings of exhaustion after a self-regulation task in an experiment serve to uphold "the motivational balance between maintaining cognitive effort on externally rewarded 'have-to' goals versus switching to more 'want-to' goals that act as form of cognitive leisure" (p. 129). This implies that competing goals are regularly compared in terms of their perceived costs and benefits. Indeed, Boksem and Tops (2008) propose that "when the perceived energetical costs of task performance come to exceed the motivation to obtain reward or avoid punishment, the present activities may be abandoned, and perhaps a potentially more rewarding activity will be engaged in" (p. 135), noting that the feeling of exhaustion corresponds to the tendency to abandon the current activity. The commonality between these models, then, is that they conceptualize exhaustion as an adaptive response to a perceived unfavorable cost-benefit ratio of the current activity (i.e., the activity nets more costs than benefits) that serves to drive behavior towards more beneficial activities.

Building on previous cost-benefit models, Kurzban et al. (2013) argue that the performance in effortful tasks is the direct result of computations of the focal tasks' costs relative to the benefits of other tasks that could be done instead. They describe subjective effort (and by extension, exhaustion) as the conscious, experienced measurement of the costs of continuing an activity. Thus, feelings of exhaustion should increase as the costs of the current task and the benefits of other tasks increase. However, is it reasonable to assume that competing goals are *always* considered in such cost-benefit computations? What about a scenario where one would rather do *anything else* other than continue with an effortful activity? In an attempt to close this gap, Hennecke and Freund (2013) propose that exhaustion arises from the perceived costs as well as the amount of resources invested in a task relative to the overall amount of available resources. In their view, exhaustion emerges from cost computations related to the currently pursued goal (i.e., how much have I already invested into this goal and how much do I still have to invest towards the desired end?). This conceptualization does not require a comparison with another goal and relates the feeling of exhaustion mainly to the *means* of goal pursuit (i.e., the amount of resources one has at one's disposal to attain a certain outcome). As of yet, however, it is unclear if opportunity costs drive exhaustion by making salient how the goal-relevant means could be spent instead or if focusing mainly on the resources spent on the goal at hand is more strongly associated with exhaustion.

Taking a Functional Approach to Exhaustion and Recovery

Following Hennecke and Freund's (2013) proposition, we define exhaustion as an adaptive motivational response arising from (non-conscious) computations regarding the means or resources one has available to pursue a given goal. According to this conceptualization, exhaustion signals to a person to disengage from an activity that might be better invested into alternative goals. In this perspective, the primary function of exhaustion is to help maintain an effective overall management of a person's multiple goals. The function of recovery lies in reducing or removing the feeling of exhaustion and its associated physical, cognitive, emotional, motivational, and behavioral responses so as to reinvigorate a person for the pursuit of more attractive goals. Accordingly, recovery can occur in different functional domains (e.g., physical, cognitive, emotional), depending on what kind of domains are affected by exhaustion.

If exhaustion serves to guide us away from further pursuing a goal with a currently unfavorable cost-benefit ratio towards a goal with a favorable cost-benefit ratio, people should start to recover when they cease the pursuit of a goal or activity with an unfavorable cost-benefit ratio. In line with this assumption, Meijman and Mulder (1998) argue that persons can only begin to recover in one functional domain once they cease all activities that contribute to the exhaustion associated with activities in that domain. For instance, a person likely recovers more efficiently from one-hour of running by avoiding rather than further engaging in physical effort. This does not mean, however, that persons should avoid *any* kind of effort following exhaustion in order to recover. For instance, physical effort may help to recover from cognitive effort. In fact, physical effort can enhance performance on a subsequent cognitive task (e.g., Brisswalter et al., 2002).

Psychological Indicators of Exhaustion and Recovery

How do we know when an activity has helped us to recover or has exhausted us? What processes might indicate the increasing costs of staying engaged in an activity whose purpose has already been fulfilled (recovery) or that has become too costly to be continued (exhaustion)? As outlined at the outset of this article, we propose three distinct yet interrelated psychological indicators of exhaustion and recovery, namely (1) perceived opportunity costs, (2) mood, and (3) subjective time perception. In the following, we discuss how these processes might relate to exhaustion and recovery.

Opportunity Costs

Everything we do carries an opportunity cost – that is, the value of the next-best alternative to the current activity. This notion goes back to the problem of *simultaneity* (i.e., not everything can be done at once) and its solution, *prioritization* (i.e., choosing one option at the expense of others; Kurzban et al., 2013). On a behavioral level, this means that we cannot pursue every goal we hold simultaneously; rather, we must always choose to pursue some goals over others at any given point in our lives. Successfully managing such conflicts in personal goals is beneficial for one’s subjective well-being (Riediger & Freund, 2004). The same principle holds true for everyday life activities. For instance, spending your evening working out in the gym carries the cost of forgoing any alternative way you could spend the evening (e.g., meeting a friend or reading a book). Indeed, this notion seems especially plausible for effortful activities: Instead of exerting effort and exhausting ourselves, we could always be doing something involving less effort. However, when we apply the same notion to relaxing activities, we are faced with a seeming paradox: Why should we think about the value of alternative activities when we are engaged in something we find relaxing? In fact, why should we engage in *anything else* but relaxing activities when given the choice? We propose a simple explanation: There comes a time when such an activity has fulfilled its goal of recovery. In order to maintain an overall effective management of our goals, it is important to notice when that time has come, so that we can avoid further investing resources into the already achieved goal of recovery. Increases in perceived opportunity costs might be one way of signaling that an activity has successfully relaxed us: Increasing the frequency of thoughts about, and the attractiveness of, alternative activities should increase the probability that a person soon thereafter disengages from the current activity and settles on a more attractive alternative.

This leads to an interesting proposition: An activity should entail no noticeable opportunity costs for as long as a person perceives it as relaxing. However, once the goal of recovery has been met, an increase in the awareness of the activity's opportunity costs might indicate to a person that it is time to disengage from the activity and engage in a more beneficial activity. For effortful activities, we argue that an effortful activity starts to become exhausting when opportunity costs begin to become conscious. In other words, the higher the perceived opportunity costs of an effortful activity, the more exhausting it is experienced.

Mood

Mood can be defined as a diffuse and objectless affective experience (Clore & Huntsinger, 2007). Mood differs from emotions in both duration and intensity, with mood typically lasting longer and being felt as less intense than emotions (Parkinson et al., 1996). Mood also comprises a core affective component that provides an informational value about the current situation as positive or negative (Russell, 2003). Morris (1992) describes mood as providing valuable information about a person's internal state and about the resources available to meet environmental challenges. Hence, one function of mood might be to signal what is going right (positive mood) or wrong (negative mood) with interacting with the environment.

According to the affect-as-information hypothesis (Clore & Huntsinger, 2007; Clore et al., 2001), mood serves as an affective feedback that, in turn, influences judgment, decision-making, and information processing. For instance, when judging an object, we may simply ask ourselves how we feel about a given object and integrate this affective feedback in our evaluations (Schwarz & Clore, 2007). Positive mood could indicate that the object is valuable and pleasant, and thereby lead to more positive evaluations. Negative mood might signal that the object is neither valuable nor pleasant, and lead to a more negative evaluation. One explanation for this is that positive mood often promotes top down, theory-based processing and a reliance on easily accessible information (e.g., knowledge, beliefs, stereotypes, expectations, primed thoughts). In contrast, negative mood tends to promote bottom up, data-based processing with a reliance on information from the external environment (e.g., Bodenhausen, Kramer, & Süsser, 1994). In a related manner, people in a positive mood tend to process incoming information relationally (i.e., cognitive, interpretive, category-level, global), whereas people in a negative mood tend to process incoming information referentially (i.e., perceptual, item-level, and local; Clore & Storbeck, 2006; Fiedler, 2001). Processing information more thoroughly might motivate people in a bad mood to locate the cause(s) of their unpleasant state, and try to change it towards a more positive state. Processing information more loosely might motivate people in a positive mood to stay engaged in their current activity, as they perceive nothing wrong with the current situation (Schwarz & Clore, 1983).

The affect-as-information approach along with the different processing styles that accompany positive and negative mood marks mood as another possible indicator of exhaustion and recovery. Assuming that engaging in a recovering activity puts people in a good mood, they should then be more likely to adopt a relational, top down processing style (Clore & Huntsinger, 2007). The positive mood state indicates that the current activity is desirable and to be continued. Once the goal of recovery is met, one's mood should become less positive and pleasant, thereby increasing the likelihood to disengage from this activity. In contrast to recovery, engaging in an effortful activity should start to worsen one's mood when the activity starts to be experienced as exhausting and thereby gradually increase the likelihood to disengage from it.

Time Perception

Time perception is highly subjective: While waiting, time seems to expand, but while being engaged in a fun activity, time seems to fly. What underlies such variations in subjective time perception? Research has mainly focused on psychological processes such as attention (Brown, 1985; Zakay & Block, 1996), arousal (e.g., Mella, Conty, & Pouthas, 2011), and affect (Droit-Volet & Gil, 2009). Much of this research has focused on experimental designs that use prospective duration judgments (i.e., being aware that a target duration needs to be timed) as indicators for subjective time perception, with timing intervals in the milliseconds and seconds range (e.g., Angrilli, Cherubini, Pavese, & Manfredini, 1997; Droit-Volet, Brunot, & Niedenthal, 2004; Noulhiane, Mella, Samson, Ragot, & Pouthas, 2007).

Results from these prospective timing studies have primarily been interpreted within the context of internal clock models (Church, 1984; Zakay & Block, 1995; Lejeune, 1998). According to these models, humans possess an internal clock mechanism that accounts for the formulation of prospective duration judgments. In short, an internal pacemaker sends "time pulses" at a steady pace into an accumulator, where the pulses are stored. The more pulses are accumulated, the longer the time interval seems to last. When the to-be-timed event is over, this internal clock compares the amount of pulses stored in the accumulator to a reference duration in our memory. The internal clock then uses this information to determine whether the target duration has lasted longer or shorter than the reference duration.

Attention plays a central role in modulating this internal clock mechanism (Zakay & Block, 1996), and researchers have extended internal clock models by including an attentional gate (Zakay & Block, 1995) or dynamic switch (Lejeune, 1998) between the pacemaker and accumulator. When we attend to time, the attentional gate or dynamic switch opens, and time units can freely flow into the accumulator. However, when we do not attend to time, the attentional gate or dynamic switch closes, and time units are not recorded. Thus, the more attention is spent on timing, the more time units are stored in the accumulator due to an opening of the gate, and the longer the target duration seems to last. The more attention is spent on non-temporal information, the less time units are stored in the accumulator due to a closing of the gate, and the shorter the target duration seems to last (Grondin, 2010).

A considerable amount of research has examined the effects of arousal and affective valence on prospective duration judgments (for a review see Droit-Volet & Gil, 2009). On the one hand, when persons are exposed to highly arousing negative stimuli for up to four seconds, they consistently overestimate the duration of these stimuli (Noulhiane et al., 2007). On the other hand, highly arousing positive stimuli often lead to underestimations in duration judgments. These findings have been interpreted in terms of the internal clock model; that is, high arousal leads to increased rate of time pulses sent into the accumulator, which leads to a higher accumulation of pulses and, as a result, longer duration estimations. However, an important limitation is that these studies use only prospective duration estimation or reproduction tasks to assess subjective time perception and only very short durations in the milliseconds to seconds range. For this reason, these study designs are not suited to explain variations in subjective time perception in everyday life activities, which are often performed for several minutes or hours.

Passage of time judgments (i.e., subjective evaluations of how quickly or slowly time passes for a person in a specific situation; Wearden, 2015) seem well suited to assess subjective time perception in everyday life activities. For instance, Droit-Volet and Wearden (2015) found that happy people report a faster momentary passage of time, whereas sad people report a slower momentary passage of time. In addition, they found a positive association between arousal and passage of time judgments: The higher the arousal, the faster time seems to pass in a situation. No age effects were found between younger and older adults in their passage of time judgments, although time seems to speed up as people age.

How is subjective time perception associated with exhaustion and recovery? Similar to the affect-as-information approach, Zakay (2014) argues that the felt pace of time during an activity provides us with information about that activity's contribution to our overall level of functioning: An elevated pace of time signals that the current activity is valuable and desired; an extended pace of time signals that the current activity might be contributing negatively to our overall level of functioning. Using the case of boredom, Zakay (2014) illustrates that when people feel bored, they start to adopt prospective timing and focus more attention to the passing of time. According to the internal clock models reviewed above, this enhanced attention to timing leads to the feeling that time drags, alerting us that something is wrong in the current environment. This alerting function of subjective time perception can be extended to the context of recovery and exhaustion: Engaging in a pleasant and recovering activity leads to less time monitoring and the feeling that time flies. In extreme cases, we might even find ourselves in a state of "flow" and not perceive the passage of time at all (Nakamura & Csikszentmihalyi, 2009). However, once the goal of recovery has been met, it should become adaptive for a person to start perceiving time as slowing. This change in time perception, coupled with increasing opportunity costs and negative mood, might indicate to the person that it is time to disengage from the activity and turn to more attractive alternatives. In addition, engaging in an activity should gradually lead to an extended time perception when it starts to become exhausting. Thus, taken together with changes in opportunity costs and mood, a change in subjective time perception during an effortful or relaxing activity might be an indicator of exhaustion or recovery.

Putting It All Together: Towards a Motivational Account of Exhaustion and Recovery

Based on the work reviewed in the prior sections, we propose that changes in mood, subjective time perception, and opportunity costs experienced during an effortful or relaxing activity indicate a person's feelings of exhaustion or recovery. This perspective on exhaustion and recovery is built on the notion that the degree of engagement in an activity is influenced by its perceived cost-benefit ratio (e.g., Boksem & Tops, 2008; Hockey, 2011; Inzlicht et al., 2014; Kool & Botvinick, 2014). As can be seen in Figure 1, a favorable cost-benefit ratio (i.e., the activity's benefits outweigh its costs) should lead to a good mood, a fast to neutral subjective time perception, and no discernible opportunity costs. This motivational state indicates to a person that the current activity is desirable and should be continued (Clore & Huntsinger, 2007; Kurzban et al., 2013; Zakay, 2014). However, once the cost-benefit ratio turns unfavorable (i.e., the activity's costs outweigh its benefits), these processes should start to change: One's mood should become unpleasant, time start to drag, and opportunity costs become more salient. This change in one's motivational state, in turn, indicates to a person that the current activity is no longer desirable and should be disengaged from. In the context of recovery and exhaustion, this disengagement process is adaptive because the outcome of a relaxing activity has been achieved (recovery) or the outcome of an effortful activity cannot be achieved with the currently available means or resources (exhaustion).

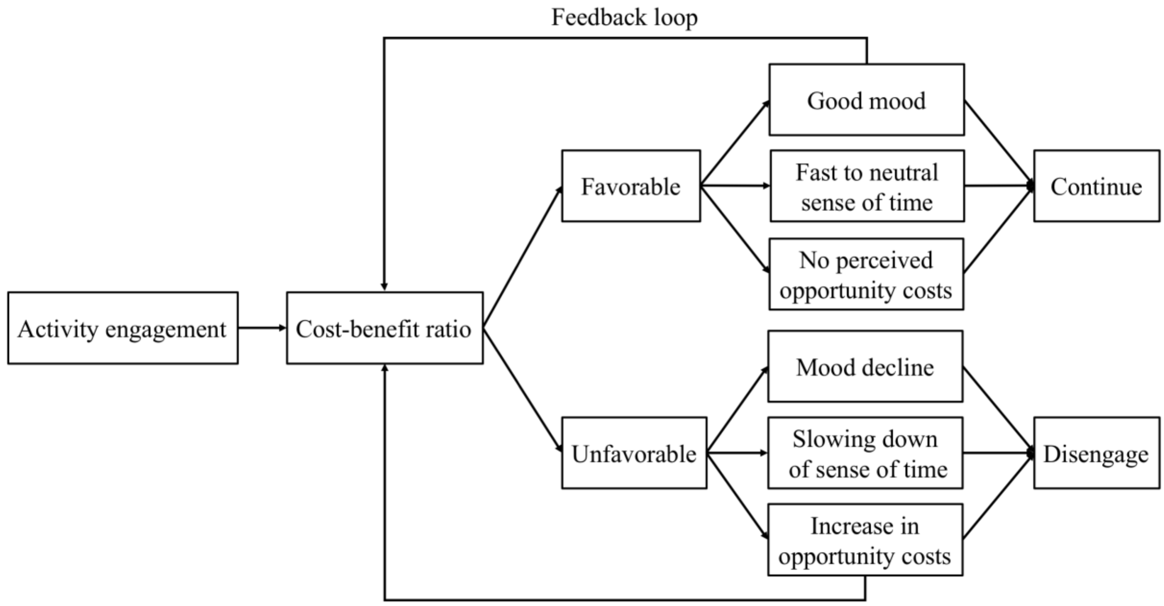

Figure 1. A motivational perspective on exhaustion and recovery: As long as the cost-benefit ratio for an activity is favorable (i.e., the activity nets more benefits than costs), the person experiences good mood, neutral to accelerated subjective time perception, and no opportunity costs. In this motivational state, the person perceives the activity as contributing to their recovery (relaxing activity) or not yet exhausting (effortful activity). The behavioral response is continued engagement in the activity. When the cost-benefit ratio turns unfavorable (i.e., the activity nets more costs than benefits), the person experiences a gradual decrease of positive mood, expanded subjective time perception, and an increase in opportunity costs. In this motivational state, the person perceives the activity as no longer contributing to their recovery (relaxing activity) or as increasingly exhausting (effortful activity). The behavioral response is eventual disengagement from the activity.

Several hypotheses can be derived from this motivational perspective:

Hypothesis 1: Engaging in a relaxing (effortful) activity gradually leads to (a) good mood, (b) the feeling that time passes fast, (c) no discernible opportunity costs. This will be experienced as recovery (absence of exhaustion).

Hypothesis 2: After a certain amount of time (i.e., when the cost-benefit ratio turns unfavorable), one will no longer perceive the activity as contributing to one's recovery (one will perceive the activity as increasingly exhausting).

Hypothesis 3: The continued engagement in an activity that is no longer perceived as contributing to one's recovery (that is perceived as increasingly exhausting) will result in (a) one's mood starting to become less pleasant, (b) the feeling that time passes more slowly, and (c) increasing opportunity costs.

Hypothesis 4: Engaging in an effortful activity gradually leads to (a) bad mood, (b) the feeling that time passes slowly, (c) increasing opportunity costs. This will be experienced as exhaustion.

The Development of Exhaustion and Recovery Across Adulthood

One of the most dramatic changes that occur across the lifespan is the changing ratio of resource gains to losses, such that gains decrease and losses increase (Baltes, 1987). This change in the availability of resources affects processes of goal setting and pursuit across the lifespan, emphasizing the trade-offs between multiple goals with increasing age (Freund & Baltes, 2000). What does this imply for the motivational approach to exhaustion and recovery proposed above? How do the psychological processes underlying exhaustion and recovery, and the occurrence and manifestation of exhaustion and recovery, change across adulthood? Next, we discuss the development of opportunity costs, mood, and subjective time perception across adulthood, and how this development may impact experiences of exhaustion and recovery at different stages in life.

Opportunity Costs Across Adulthood

A central tenet of lifespan psychology holds that development comprises the presence of both gains and losses in all phases of life (Baltes, 1987). Yet, as people grow older, biological and cognitive functioning decline, and the gains/losses ratio is increasingly weighted towards losses (Baltes, Lindenberger, & Staudinger, 2006). Ebner, Freund, and Baltes (2006) showed that changes in the ratio of gains and losses across adulthood relate to age-related changes in personal goal orientation. This means that younger adults, being at the peak of biological and cognitive functioning, mainly invest their resources in growth- and gain-oriented goals (e.g., broadening their social networks, acquiring broader knowledge, advancing their careers), whereas middle aged and older adults, facing increasing declines in resource availability, primarily invest their resources in goals aimed at maintaining their current level of functioning and preventing further losses. Further supporting the age-related shift in goal orientation, Freund (2006) found experimental evidence that older adults persist longer than younger adults in tasks designed to regain lost resources, whereas younger adults persist longer than older adults in tasks designed to optimize their performance.

If fewer resources are available with increasing age, the importance of not wasting any of them in superfluous goal pursuit should become more and more imperative with age. Therefore, increases in opportunity costs during an effortful or relaxing activity should become more salient in older compared to young adulthood. If this is true, older adults should feel exhausted faster when pursuing effortful activities and, consequently, also disengage faster from the exhausting activity than younger adults. Being more sensitive to opportunity costs might be adaptive for older adults as it helps them to avoid exhaustion-related losses. This assumption is supported by evidence that older adults disengage faster from blocked and unachievable goals (Wrosch, Scheier, Miller, Schulz, & Carver, 2003) and prioritize more efficiently between conflicting goals (Freund & Tomasik, 2019).

Taken together, opportunity costs might be more salient for older adults than for younger adults. This, in turn, might indicate that older adults exhaust more easily and for this reason spend less time in an exhausting activity than younger adults. Furthermore, older adults might spend more time in a recovering activity (i.e., an activity designed to regain lost resources), which might indicate that older adults recover more slowly compared to younger adults.

Emotional Experience Across Adulthood

Research from the past 15 years has shown that older adults – compared to younger adults – generally report more positive and less negative emotions in their everyday lives (Carstensen et al., 2011). Socioemotional selectivity theory (Carstensen, Isaacowitz, & Charles, 1999) offers a possible explanation for older adults' stable and largely positive emotional well-being: According to the theory, as people grow older and their perceived future time horizons shorten, they start to place more importance on emotional and hedonic goals that are achievable in the present rather than in the future. This emphasis on emotionally meaningful goals, such as seeking a greater appreciation of life and engaging in more meaningful social relationships, improves older adults' emotional experience by reducing the occurrence of negative emotions and enabling a steady rate of positive emotions.

On the basis of socioemotional selectivity theory, one might argue that older people – by actively shaping their environment toward more positive and less negative experiences – create more opportunities to engage in pleasant and recovering activities and less instances to engage in exhausting activities. Furthermore, older adults might be more efficient at regulating their emotions than younger adults (Urry & Gross, 2010). For instance, Larcom and Isaacowitz (2009) found that following a negative mood induction, older adults down-regulated negative emotions and up-regulated positive emotions faster and for longer than did younger adults. Such improved emotion regulation abilities might have an influence on older adults' experienced recovery and exhaustion in everyday life: older adults might (1) be more efficient in repairing negative mood arising from exhaustion, and (2) stay longer in up-regulated positive mood states than younger adults. With regard to recovery, older adults might thus recover faster and stay recovered for longer than younger adults.

Time Perception Across Adulthood

For more than a century, psychologists have attempted to explain the feeling that time seems to speed up as we get older (e.g., James, 1890; Draaisma, 2004). However, empirical results regarding a speeding up of time with age are controversial. For instance, Wittmann and Lehnhoff (2005) found that momentary perceptions of the passage of time seem to accelerate with age, whereas studies investigating the retrospective recall of time passage tend to report age-related accelerations in time perception only when investigating the passage of the previous 10 years compared to smaller time intervals (e.g., Janssen, Naka, & Friedman, 2013).

The increasing losses in biological and cognitive functioning in older adulthood might have an influence on prospective duration judgments as theorized by internal clock models. For instance, decreases in basal metabolism in older adulthood (Altman & Dittmer, 1968) might lead to decreased activities of older adults' internal pacemakers (Block, Zakay, & Hancock, 1998), which would in turn result in shorter time estimations in prospective duration tasks. Furthermore, age-related decreases in attentional capacity (e.g., Lustig, 2003) and information processing speed (e.g., Verhaeghen & Salthouse, 1997) might cause the hypothesized attentional gate between the pacemaker and accumulator to close more frequently, and, as a result, again lead to shorter duration estimations (for a meta-analysis on aging and duration judgments, see Block et al., 1998).

To date, only few studies have examined age-related differences in everyday life passage of time judgments, and the available results are mixed. For instance, in two experience sampling studies, Droit-Volet and Wearden (2015, 2016) found no significant acceleration of time passage during everyday life activities for older adults compared to younger adults, despite the fact that participants generally agreed with the notion that time seems to pass more quickly as people age. In contrast, Wittmann and Lehnhoff (2005) reported a significant acceleration of momentary passage of time perceptions in older versus younger adults. Thus, it is as of yet unclear whether older and younger adults differ in their perceptions of time, and how duration estimations and passage of time judgments might change across adulthood.

The length of the time period during which recovery or exhaustion occur might serve as an important informational cue that tells people how much they have recovered or become exhausted (Zakay, 2014). A person who perceives time to pass more quickly, then, might feel more recovered (less exhausted) after engaging in a relaxing (effortful) activity than a person who perceives time to pass more slowly during the same activity and time span. Assuming that older adults perceive time to pass more quickly than younger adults in everyday life activities, one might thus argue that older adults feel more recovered (less exhausted) than younger adults after a certain amount of time spent in the same relaxing (effortful) activity.

Summary

With regard to the development of exhaustion across adulthood, it seems plausible that opportunity costs become more salient in old age: Age-related changes in resource availability (i.e., losses of important physical and cognitive functioning; Heckhausen, Dixon, & Baltes, 1989; Mustafić & Freund, 2012a) as well as a shift in time perspective (i.e., increased salience of the fact that life-time is running out; Lang & Carstensen, 2002) may motivate older adults to focus their remaining energy and time on avoiding further losses (Freund & Baltes, 2000). Therefore, it seems adaptive if older adults feel exhausted more easily, as it would prompt them to disengage from a taxing activity earlier, and in so doing better protect their remaining resources. On a different account, older adults' subjective time perception might be accelerated, so that they might perceive everyday life activities to go by faster, and as a result feel less exhausted after the same time span than younger adults.

With regard to recovery across adulthood, one could argue that older adults persist longer in a recovering activity (e.g., Freund & Tomasik, 2019). This might be the case for several reasons. First, older adults might simply need more time to recover compared to younger adults. Second, older and younger adults might recover at similar rates, yet older adults might perceive the changes in recovery indicators (i.e., increasingly negative mood, expanded subjective time perception, increase in opportunity costs) more slowly than younger adults. Third, older adults might engage longer in recovering activities because their time perception is accelerated.

General Conclusion

Taking a motivational approach to exhaustion and recovery, we propose that changes in mood, subjective time perception, and opportunity costs experienced during an activity are central indicators of recovery or exhaustion. This approach allows to formulate empirically testable hypotheses. Moreover, embedding the motivational approach in the context of adult development and aging, we suggest that exhaustion and recovery change systematically across across adulthood. To our knowledge, this is the first psychological account that integrates exhaustion and recovery as separate constructs and that provides a comprehensive account of the psychological indicators that serve the function to indicate when an activity should be abandoned because it no longer contributes sufficiently to goal achievement. We hope that this motivational account of recovery and exhaustion will serve as the theoretical starting point for empirical research that will contribute to a better understanding of exhaustion and recovery across adulthood.

PART II: THE ROLE OF MOOD AND OPPORTUNITY COSTS FOR SUBJECTIVE RECOVERY

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This article has been submitted for publication (2019) in a peer-reviewed journal and is currently under review. Please do not copy or cite without permission of the authors.

Abstract

Four methodologically diverse studies investigated the role of mood, opportunity costs, and subjective time perception for recovery from exhaustion. Study 1 (N = 356) explored people's lay beliefs in open-ended responses about what thoughts, feelings, and behaviors indicate recovery. Study 2 (N = 134) examined within-person associations between changes in recovery, mood, opportunity costs, and time perception following an exhaustion induction. Studies 3 and 4 (N_{Study3} = 129; N_{Study4} = 150) experimentally tested the hypothesis that opportunity costs are related to recovery. We consistently found a positive association between changes in mood and recovery, but no associations between opportunity costs or time perception and recovery. Furthermore, despite a successful manipulation of opportunity costs in Study 4, the perceived value of competing activities was unrelated to recovery. However, increasing opportunity costs were associated with increasing exhaustion. Taken together, these results suggest that changes in mood are an important indicator of recovery and provide first empirical support that opportunity costs influence experienced effort.

Introduction

Imagine an overworked lecturer grading her students' essays on her commute home. Exhausted from the day's events, she soon finds herself in need of a break. She closes the laptop, puts on noise-cancelling headphones, and indulges in her favorite music playlist. Eyes shut, she begins to relax. Her mood gets better. She is pleasantly surprised how fast time had passed when the train arrives at the next station. Then, halfway through the playlist, she starts to feel bored, the current song seems to go on for too long, and she catches herself thinking about resuming essay grading. Thus, she puts away her headphones and opens the laptop again, ready to spend more effort.

How did this lecturer know when she was sufficiently recovered to resume work? We (Cardini & Freund, 2019a) have recently proposed that people infer their recovery progress from three psychological indicators: (i) *perceived opportunity costs* (i.e., the subjective costs of foregoing attractive alternatives compared to the benefits of staying engaged in the focal activity), (ii) *mood*, and (iii) *subjective time perception*. To preview, as long as an activity (e.g., listening to music) contributes to our recovery, we are in a good mood, perceive time as passing quickly, and experience no opportunity costs. However, once the activity no longer contributes significantly to further recovery, our mood starts to decline, time to extend, and opportunity costs to become more salient. According to our model, these perceived changes indicate recovery and, as a result, an increased motivation to disengage from the focal activity.

In this paper, we present first empirical research on the importance of mood, opportunity costs, and subjective time perception as psychological indicators of recovery. In what follows, we introduce our motivational approach to recovery as signaling goal disengagement and detail the theoretical rationale for choosing perceived opportunity costs, mood, and subjective time perception as indicators of recovery.

A Motivational Perspective on Exhaustion and Recovery

Perhaps the most prominent approach to exhaustion and recovery assumes the existence of a limited domain-general resource that is depleted through usage and then needs to be restored (e.g., Baumeister et al., 1998; Kaplan, 1995; Kaplan & Berman, 2010; Ryan & Deci, 2008). However, recent meta-analytic work (Carter et al., 2015; Carter & McCullough, 2014) and preregistered replication efforts (Hagger et al., 2016; Lurquin et al., 2016) have cast serious doubt on this notion. In fact, offering incentives (Boucher & Kofos, 2012), inducing positive affect (Tice et al., 2007), and adopting a non-limited theory of willpower (Job et al., 2010) counteract exhaustion-related decrements in task performance, speaking against the limited resource model. Taken together, these findings suggest that exhaustion and recovery are mainly subjective and do not reflect an objective state of depletable resources.

Recent approaches have focused on the role of *motivation* for exhaustion (Hockey, 2013; Inzlicht et al., 2014; Kool & Botvinick, 2014; Kurzban et al., 2013). Common to these motivational accounts is the hypothesis that the subjective cost-benefit ratio of an activity is closely associated with the experience of effort and exhaustion. In short, as long as an activity is perceived as generating more benefits than costs, people enjoy engaging in it. On the contrary, when the activity is perceived to incur more costs than benefits, it becomes unpleasant and tiresome. Similar to boredom (Bench & Lench, 2013), such theories conceptualize exhaustion as a “stop-emotion” with the primary function to guide behavior away from costly to more rewarding activities (van der Linden, 2011).

While these motivational accounts provide a compelling explanation for exhaustion, they have largely neglected to address the flip side of the coin – *recovery*. If exhaustion indicates that the current activity should be discontinued due to its unfavorable cost-benefit ratio, then does recovery indicate that the current activity should be continued because its cost-benefit ratio is favorable? And if this were the case, how would we know when recovery is achieved? In other words: What prevents us from pursuing relaxing activities indefinitely? In an attempt to close this gap, we have recently proposed three psychological indicators of recovery (i.e., perceived opportunity costs, mood, and subjective time perception), which we will introduce next.

Psychological Indicators of Recovery

Perceived Opportunity Costs

Given that our physical and cognitive capacities are limited, we are constantly faced with the challenge of prioritizing some actions, activities, or goals at the expense of others. Successfully managing such goal conflicts in daily life is important for psychological well-being (Riediger, Freund, & Baltes, 2005). By necessity, prioritization introduces costs and benefits. For instance, choosing to spend one's evening revising a manuscript over hanging out with friends comes with the benefit of working toward advancing one's career but carries the cost of neglecting valuable social relationships. While we acknowledge that these costs and benefits are highly subjective, situation-specific, and thus difficult – if not impossible – to systematize, we agree with Kurzban et al. (2013) that the ultimate price of engaging in any activity is the time forgone on the next-best alternative – an activity's *opportunity costs*.

Experiencing opportunity costs during an ongoing task is associated with an increase in perceived effort, a decrease in perceived task utility, and ultimately leads to task disengagement (Hofmann, Rom, Katzir, & Diel, 2019). Exerting effort is usually experienced as aversive (Kurzban, 2016, but see Inzlicht, Shenhav, & Olivola, 2018) and people avoid unnecessarily exerting effort (Richter et al., 2016). Thus, perceiving opportunity costs might serve the adaptive function of signaling that one's time and effort are better spent on another task. Applying this notion to recovery, we maintain that experiencing opportunity costs during a relaxing activity indicates that the activity's perceived cost-benefit ratio has turned unfavorable (i.e., is no longer contributing to recovery) and should thus be disengaged from.

Mood

According to the affect-as-information approach (Clore et al., 2001), *mood* provides valuable information about one's current environment. Positive mood, along with an increased reliance on global and heuristic cognitive processing, indicates a safe and benign environment. Negative mood, along with an increased reliance on local and systematic cognitive processing, signals a problematic environment (Clore & Huntsinger, 2007; but see Huntsinger, Isbell, & Clore, 2014). Based on this approach, we propose that people take their current mood as information about their recovery progress. In particular, people are more likely to perceive their current environment as contributing to their recovery when they are in a good mood. However, once the relaxing environment does no longer significantly contribute to recovery, we posit that people's mood starts to get worse, thereby indicating that the environment has become problematic and is no longer contributing to recovery.

Reinforcing this notion, the mood-as-input approach (Martin, Ward, Achee, & Myer, 1993) maintains that positive mood tells us to continue and negative mood to cease an activity, provided that mood reflects one’s current level of enjoyment. Thus, when deliberating whether they should stay engaged in a relaxing activity, people may ask themselves “Am I still enjoying this?” and answer in the affirmative when in a good mood and in the negative when in a bad mood, prompting them to continue or cease the activity, respectively. Therefore, we conceptualize positive mood as an indicator of the current state of recovery.

Subjective Time Perception

Similar to mood, Zakay (2014) argues that *subjective time perception* (i.e., the felt pace of time) during an activity provides us with information about that activity’s utility: An accelerated subjective time perception ascribes value to the current activity (“time flies when having fun”); an extended subjective time perception indicates a lack of value (“time drags when being bored”). Indeed, people take their perception of time as input for hedonic evaluations: Irrespective of their baseline valence, tasks are consistently rated as more pleasant when they end sooner than expected and more unpleasant when they last longer than expected (Gable & Poole, 2012; Sackett, Meyvis, Nelson, Converse, & Sackett, 2010).

The motivational implication of subjective time perception, then, might be to continue an activity when the pace of time is perceived as accelerated and disengage from an activity when the pace of time is perceived as extended. Accordingly, we propose that people are more likely to perceive their current environment as contributing to their recovery when they experience an acceleration of subjective time perception, and as not contributing to recovery anymore when their perception of time begins to extend. Taken together, along with increasingly negative mood and salient opportunity costs, we argue that an extension in subjective time perception is taken as an indication that the current activity has reached its saturation point and that time and energy are better spent on another activity.

The Present Studies

Four studies investigated the role of perceived opportunity costs, mood, and subjective time perception for recovery. In Study 1, we explored people’s lay beliefs about the indicators of exhaustion and recovery. In Studies 2, 3, and 4, we induced exhaustion experimentally and in the subsequent recovery period assessed the co-occurrence of subjective recovery and its proposed indicators over time. Doing so allowed us (1) to test the hypotheses about the time courses of recovery, opportunity costs, mood, and time perception, as well as (2) to examine which of the three indicators is the most relevant for the experience of recovery. We had no a priori hypothesis about which of the proposed indicators might be most strongly associated with recovery. Thus, our overarching aim was to achieve as parsimonious an account of recovery as possible.

Across the studies, we employed a methodologically diverse approach: In Study 1, we explored the indicators of exhaustion and recovery qualitatively using inductive content analysis (Hsieh & Shannon, 2005). We designed Study 2 as a laboratory experiment encompassing an exhaustion and recovery period in a controlled environment with the aim to track the specific time courses (and their covariations) of recovery, opportunity costs, mood, and time perception. Building on these correlative results, in Studies 3 and 4 we sought to establish a causal relationship between opportunity costs and recovery by testing whether manipulating opportunity costs before and during the recovery period systematically impacts the subjective speed of recovery.

All four studies adhered to the guidelines of the local ethics committee, including the signing of an informed consent form and a debriefing after the study. We disclose all measures, manipulations, and exclusions for these studies in the main text. All the data was collected prior to data analysis.

Study 1

We began our empirical investigation by exploring people's lay beliefs about the indicators of exhaustion and recovery. Lay beliefs are scientifically informative because they can have a substantial impact on cognition, behavior, and health (Zedelius, Müller, & Schooler, 2017). The aim of Study 1 was to examine (1) the most frequently mentioned indicators of exhaustion and recovery, and (2) whether these lay beliefs converge or diverge from the indicators we have proposed (Cardini & Freund, 2019a).

Method

Participants. The data are based on a subsample ($N = 356$) of a larger study targeting the factorial structure of exhaustion and recovery items stemming from various questionnaires (Cardini, Knecht, & Freund, 2019). Participants in this subsample were aged between 18 and 72 years ($M = 45.15$, $SD = 15.29$; 43% female). They were recruited from an online access panel by a German research agency (www.respondi.de). Participants were reimbursed according to the agency's regulations (3.20 Euros excluding incentives).

Measures. The measures of interest for this study were two open-ended questions that read "*How do you personally know when you are exhausted (recovered)? What kinds of feelings, thoughts, and behaviors indicate to you that you are exhausted (recovered)?*"

Procedure. After giving their informed consent and filling out a sociodemographic questionnaire, we asked participants to define exhaustion and recovery in their own words and to write down what, to them, indicates exhaustion and recovery. Not part of the current study are the following measures: The frequency with which participants reported to experience exhaustion and recovery in different functional domains (i.e., physical, cognitive, emotional, social, and motivational) in their everyday lives; a list of the selected exhaustion (recovery) items stemming from various published scales.

Statistical analysis. We used an inductive content analysis approach (Hsieh & Shannon, 2005). The first author read each open statement and derived coding categories based on recurring words or sentences (e.g., "*When I'm exhausted I feel tired*" or "*When I'm recovered I'm in a good mood*"). This procedure yielded 42 categories for exhaustion (e.g., tiredness) and 43 categories for recovery (e.g., good mood). Both authors then further divided the categories into six functional domains (i.e., physical, cognitive, emotional, social, motivational, behavioral). For example, tiredness was characterized as physical (Ortony et al., 1987), while good mood was characterized as emotional. In a next step, a trained research assistant and the first author independently identified key words from each open statement (e.g., "*tired*" or "*good mood*"). These key words represent the unit of analysis. $N = 916$ key words were derived for exhaustion, and $N = 893$ key words for recovery. The agreement was high, with both coders selecting the same key words for 92% of the freely generated sentences. Finally, the research assistant and the first author independently coded each key word into one category. Key words that did not match any existing category were either coded into an “other” category in the respective functional domain or into a “rest” category if the key word did not match any functional domain.

Results

The inter-rater reliability was good with Cohen’s $\kappa = .86$ for recovery ($z = 97.60$, $p < .001$) and $\kappa = .83$ for exhaustion ($z = 104.00$, $p < .001$). Disagreements were solved through consensus. The relative frequency of key words coded into the various categories is depicted in Figure 2. As can be seen, regarding exhaustion, the most frequently mentioned indicators were tiredness, low energy, listlessness, difficulty concentrating, bad mood, and irritability. Only 1.1% of key words described opportunity costs (i.e., wanting to do something else). None of the participants mentioned subjective time perception as an indicator of exhaustion. Taken together, 41% of the mentioned exhaustion indicators were physical (including tiredness), and of the psychological indicators 20% were emotional, 13% cognitive, 10% motivational, 10% behavioral, 4% social, and 2% could not be categorized.

Regarding recovery, the most frequently mentioned indicators were good mood, zest for action, high energy, and relaxation. As was true for exhaustion, opportunity costs were mentioned very rarely (0.3%). None of the participants mentioned subjective time perception as an indicator of recovery. Taken together, 24% of the mentioned recovery indicators were physical, and of the psychological indicators 31% were emotional, 17% motivational, 14% cognitive, 8% behavioral, 2% social, and 4% could not be categorized.

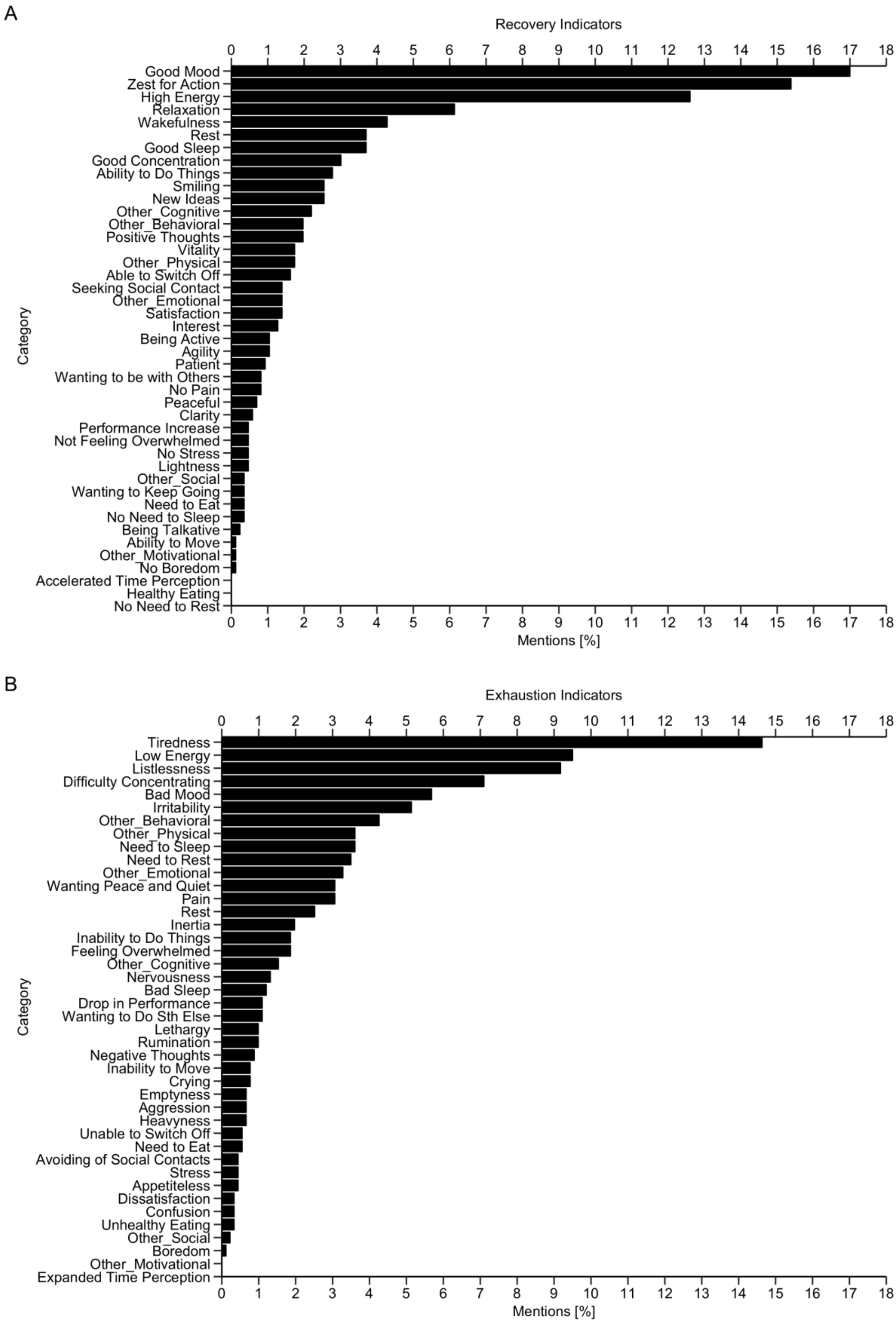

Figure 2. Relative frequencies of the mentioned recovery ($N = 893$; panel A) and exhaustion indicators ($N = 916$; panel B).

Brief Discussion

The results of Study 1 suggest that out of the three proposed indicators, mood seems to be the most frequently experienced indicator of recovery. In fact, being in a good mood was the most frequently mentioned indicator out of all the recovery indicators. In contrast, people did not come up with subjective time perception and opportunity costs as salient indicators of recovery. However, given that people are not necessarily aware of the processes underlying their psychological functioning (Nisbett & Wilson, 1977) and often neglect opportunity costs in decisions involving the use of limited resources, such as money (Frederick, Novemsky, Wang, Dhar, & Nowlis, 2009; Plantinga, Krijnen, Zeelenberg, & Breugelmans, 2018; Spiller, 2011), in a next step we empirically tested if opportunity costs, mood, and subjective time perception predict how recovered people feel.

Study 2

Designed as a more direct test of the proposed account, in Study 2 we investigated the associations between subjective recovery, mood, activity valence, time perception, and opportunity costs as they unfold during a recovery period. We first exhausted participants by means of a 20-minute high intensity interval training. Before and after the training, we assessed participants' perceived exhaustion as a manipulation check. Immediately afterwards, they watched a 25-minute relaxing video on a computer while carrying noise-cancelling headphones playing very tranquil music. We assessed the variables of interest ten times every two minutes during this recovery period. This design enabled us to analyze the time courses of recovery, mood, activity valence, time perception, and opportunity costs, as well as the associations between the random slopes of the variables (i.e., the degree to which the variables "travel together" during the recovery period).

We hypothesized that the recovery time course is best described by a concave function of time (i.e., participants recover at first, but will at some point stop recovering and even start to feel less recovered as time goes on). To be able to capture this trajectory of recovery, we chose a long recovery period of 25 minutes to guarantee that participants could fully recover from the induced short-term exhaustion. We chose an excerpt of the 1999 undersea documentary *Coral Sea Dreaming* (Small World Music, Inc.) as the relaxing activity. This documentary features beautiful visuals of Australia's Great Barrier Reef and tranquil instrumental music. Prior research has shown that this documentary can – on average – successfully recover participants in as little as seven minutes following an effortful task (Piferi, Kline, Younger, & Lawler, 2000). Based on the psychological indicators we proposed for the experience of exhaustion and recovery, we also expected that, once the goal of recovery is achieved, mood and activity valence begin to gradually decrease, time perception to expand, and opportunity costs to increase, as a signal that the present activity's cost-benefit ratio has become unfavorable (i.e., nets more costs than benefits) and should therefore be discontinued.

Method

Participants. An a-priori power analysis with G*Power (Version 3.1; Faul, Erdfelder, Buchner, & Lang, 2009) indicated that we needed at least 119 participants to detect a main effect of a within-person factor with a small population effect size (Cohen's $f = 0.10$), 95% power and a 5% error probability in a repeated measures design consisting of ten measurement occasions. We included every person that signed up for the study provided that s/he was at least 18 years old, physically healthy, and reported no diagnosed psychological disorder at the time. This resulted in a sample of $N = 134$ adults ($M_{age} = 23.93$ years, $SD = 5.04$, 74% female). The sample consisted largely of students who participated for course credit (85%). In general, participants reported relatively high physical fitness ($M = 3.30$, $SD = .78$, on a scale from 0 [*not fit at all*] to 5 [*very fit*]).

Measures.

Dispositional exhaustion and recovery. The General Exhaustion and Recovery Scale (Cardini et al., 2019) measures dispositional exhaustion and recovery as two separate dimensions. The exhaustion dimension consists of 8 items (e.g., "*In general, I feel weak*"; α = .93). The recovery dimension consists of 5 items (e.g., "*In general, I feel energized*"; α = .82). Items are measured on a scale from 0 (*not at all*) to 5 (*very much*). Participants in this sample reported relatively high dispositional recovery (*M* = 3.43, *SD* = 0.59) and low dispositional exhaustion (*M* = 1.06, *SD* = 0.74).

Dispositional mood state. The Multidimensional Mood State Questionnaire (German short version; Steyer, Schwenkmezger, Notz, & Eid, 1997) measures three bipolar dimensions of psychological functioning: Wakefulness-tiredness (4 items, α = .84), good mood-bad mood (4 items, α = .84), and calmness-nervousness (4 items, α = .80). Sample items are "*In general, I feel rested*" for awake-tired, "*In general, I feel content*" for good mood-bad mood, and "*In general, I feel composed*" for calm-nervous. Items are measured on a scale from 0 (*not at all*) to 5 (*very much*). Participants in this sample reported relatively high scores of dispositional awakeness (*M* = 3.28, *SD* = 0.94), good mood (*M* = 3.91, *SD* = 0.77), and calmness (*M* = 3.35, *SD* = 0.92).

Dependent variables. We operationalized each dependent variable as a bipolar visual analogue scale ranging from -5 to +5, with a neutral zero point in the middle (Russell & Carroll, 1999). We decided for bipolar and against bivariate affective state items for the following reason: In his comprehensive review on mixed emotions, Russell (2017, p. 116) concludes that "in most circumstances a person feels either good or bad but not both," adding that mixed emotions occur only in rare events, such as "when a stimulus event is highly salient (a powerful film, college graduation and so on)."

The recovery item read "*How do you feel right now?*" with -5 (*very exhausted*) to +5 (*very recovered*) as verbal anchors. The mood item was "*What is your momentary mood?*" with -5 (*very bad*) to +5 (*very good*), the activity valence item "*How pleasant is this activity right now?*" with -5 (*very unpleasant*) to +5 (*very pleasant*), the time perception item "*How does time pass for you right now?*" with -5 (*very slowly*) to +5 (*very fast*), and the opportunity costs item "*Right now, would you rather…*" with -5 (*continue this activity?*) to +5 (*do something else?*) as verbal anchors. The bipolar scales allowed participants to indicate the intensity of their feelings towards one pole, while also allowing for the possibility of a neutral state (i.e., the zero point), indicating that neither of the poles were presently experienced. Within-person reliabilities were good (R_{Cn}s between .81-.83; Cranford et al., 2006), indicating that systematic change over time was reliably measured by these variables.

Time as independent variable. The time variable was coded from 0 to 9, such that 0 was the first measurement occasion during the recovery period (i.e., 30 seconds into the video) and 9 was the last measurement occasion (i.e., 18 minutes and 30 seconds into the video). The time points were equally spaced (i.e., two minutes). This scaling of time implies that a linear slope for time estimates the change in the dependent variable every two minutes.

Procedure. Participants first filled out an online screening questionnaire, where they read a detailed description of the study and gave their informed consent for participation. Next, they filled out a sociodemographic questionnaire, reported on their perceived physical fitness, weekly exercise frequency, dispositional exhaustion and recovery (Cardini et al., 2019), and filled out the trait version of the Multidimensional Mood State Questionnaire (Steyer et al., 1997).

The main part of the study was conducted in two adjacent laboratory rooms in groups with up to 12 participants. Participants first filled out a baseline occasion of the paper-and-pencil items. Next, they participated in a 20-minute high intensity interval training (adopted from Kaftan & Freund, 2019). It consisted of a four-minute training unit that was repeated five times. One training unit consisted of a bout of physical exercises (e.g., jumping jacks, push-ups, plank, sit-ups, high knees). Each exercise was maintained for 20 seconds and followed up with 10 seconds of rest. Immediately upon finishing the training, participants filled out the second occasion of the paper-and-pencil items. Next, participants were quickly guided into another room, where they watched a relaxing aquatic video on a computer with noise-cancelling headphones. Thirty seconds into the video, the dependent variable items popped up in a small space on the right side of the computer screen (see Figure 3), which participants were instructed to answer as quickly as possible. The items appeared every two minutes during the video, resulting in a total of ten assessments. The video ended after 25 minutes. Participants then rated how much they enjoyed the content of the video, the music, the volume, the pop-up questions, and the degree to which the video contributed to their recovery. Lastly, they were debriefed and reimbursed (one course credit or 15 Swiss francs).

Statistical analysis. We analyzed the time course of the dependent variables using multilevel growth curve models with measurement time as independent variable, accounting for an autocorrelative error structure (AR[1]) and for heteroscedasticity. To assess correlated change between the variables, we extended these analyses to a multivariate multilevel growth curve model that estimates the time course of all variables simultaneously. We conducted all analyses in R (R Core Team, 2018). For the univariate analyses, we used the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018). For the multivariate analysis, we used the Bayesian brms package with default priors (Bürkner, 2017), as this package tends to produce more stable estimates for multilevel models with complex variance-covariance matrices (Bürkner, 2017). We followed the suggestions of Bolger and Laurenceau (2013) for reporting multilevel analyses.

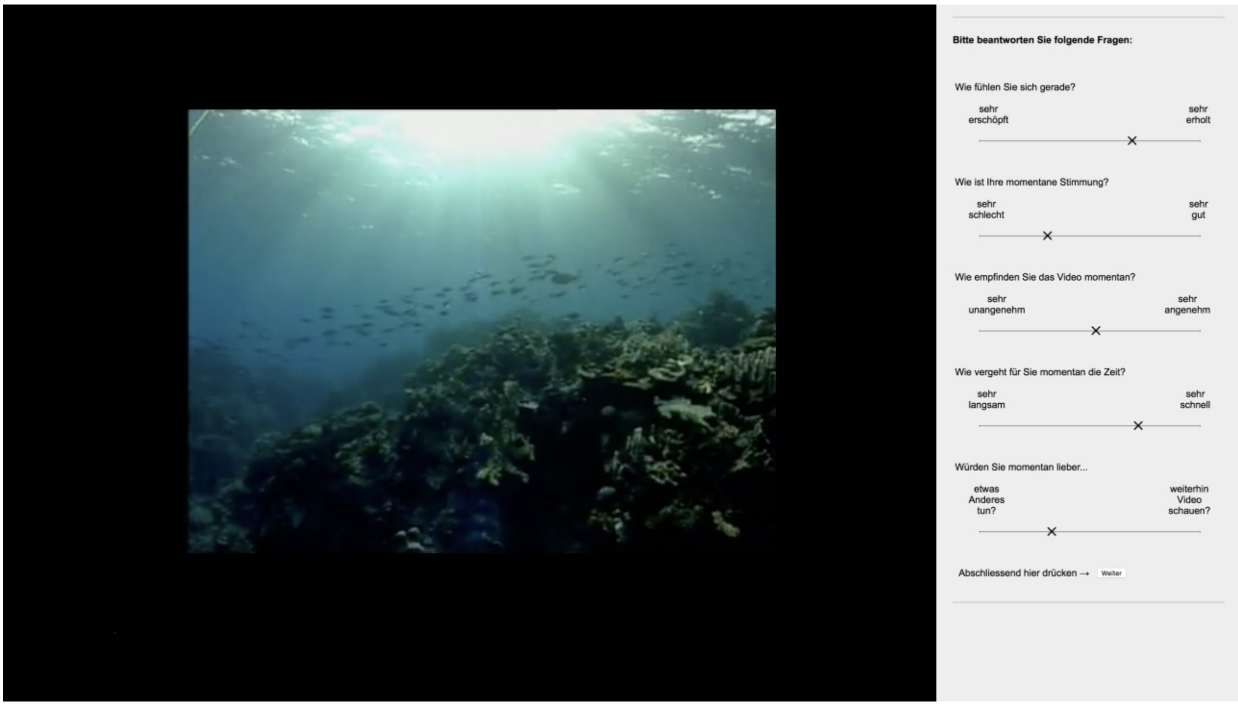

Figure 3. Screenshot of the computer screen during the recovery period (Study 2). The dependent variable items appeared every 2 minutes in the grey area of the screen.

Results

Exhaustion manipulation check. Participants reported a significant decrease in recovery (increase in exhaustion) after the training (M = -1.51, SD = 2.19) compared to before (M = 1.07, SD = 2.03), $t(133) = 10.94$, $p < .001$, 95% CI of the mean difference [2.11, 3.04], d = 0.82, 95% CI [0.57, 1.07]. Thus, the training successfully induced exhaustion. In comparison, the other dependent variables did not change meaningfully on average before vs. after the training ($|d|$s between 0.02 to 0.26; see Table A1 in Appendix A).

Preliminary analyses. The initial multilevel analysis dataset consisted of N = 134 (participants) x 10 (measurement occasions) = 1,340 observations. Inspection of the scatterplots, person by person, indicated that due to a very infrequent technical failure, four persons had missing data for one up to five measurement occasions. Thus, the final dataset consisted of 1,328 observations.

Model building. All dependent variables showed substantial between-person variance (ICCs between .57 and .71), confirming the nested structure of the data (measurement occasions nested in persons) and necessitating the use of multilevel modeling. We began the model building process by comparing random-intercept-only models to random-intercept-and-slope models for each dependent variable. In a next step, we added a simple autocorrelative error structure (AR[1]) to the models. Then, we tested whether the models should account for heteroscedasticity. Given that these models are nested, we decided on the best-fitting model using the chi-square likelihood ratio test. The best-fitting models across all dependent variables were random-intercept-and-slopes models that account for autocorrelation, but not for heteroscedasticity. In other words, participants varied substantially on all dependent variables with regard to their initial intercepts (i.e., 30 seconds into the video), as well as in their rate of change over the recovery period.

In the final model-building step, we tested which polynomial degree (i.e., linear, quadratic, cubic) best characterized the time course of the dependent variables. For each dependent variable, we compared the model with a linear fixed effect of time with a model encompassing both a linear and quadratic fixed effect of time, and so on. Since these comparisons involve non-nested models (i.e., different fixed effects structures), we decided on the best-fitting model using the AIC and BIC, with lower values indicating better model fit.

Modeling the time courses. The results for the time courses are shown in Table 1 and Figure 4. Table 1 has two sets of parameter estimates. The first set, the fixed effects, estimate the results for the average person in the sample. These fixed effects are represented by the thick black lines in Figure 4. The second set in Table 1 are the random effects. These describe variation at two levels of analysis: At the between-person level, they model the extent to which persons deviate from the typical person in the sample. At the within-person level, they model the extent to which the raw data varies from the values predicted by the model. The between-person random effects are visualized in Figure 4 by the variability in individual regression lines (thin grey lines) from the average regression line.

As can be seen in Table 1, the fixed time course of recovery was best described by a cubic function of time: The typical participant had an initial level of recovery of 0.76 units on the -5 (*very exhausted*) to +5 (*very recovered*) scale. This typical participant then showed an initial 0.67 units increase in recovery (linear slope), followed by a 0.16 units degree of curvature (quadratic slope), and finally reported another 0.01 units increase in recovery (cubic slope). The critical time values (i.e., those values of time where the slope of the cubic function is zero) were approximately located at 4.5 minutes and 14.5 minutes. Thus, the typical person recovered for the first four and a half minutes, and afterwards reported a decline in recovery until 14.5 minutes into the video, and from then on reported another increase in recovery.

The fixed mood and activity valence time courses were similar to each other: Participants' mood and the perceived pleasantness of the video showed a linear decline over the recovery period but were positive throughout the entire duration of the relaxation period. The fixed time perception trajectory started out near the neutral zero point and decreased strongly as time went on, so that by the end of the video, participants reported a strong feeling that time was passing very slowly.

The fixed opportunity costs time course started below the neutral zero point, indicating that initially, the average participant wanted to continue watching the video. As time went on, however, the opportunity costs started to strongly increase and crossed the neutral zero point (i.e., started to become salient) at six and a half minutes into the video.

Table 1

Multilevel Growth Curve Model Estimates (Standard Errors in Parentheses) for the Dependent Variables.

	Study 2 (*N* = 134)					Study 3 (*N* = 129)				Study 4 (*N* = 150)					
Fixed effects	RE	MO	TP	OC	VA	RE	MO	TP	OC	PRE	MO	TP	OC	MRE	IN
Intercept	0.76	**2.35**	0.30	**-1.85**	**2.16**	0.01	**2.24**	-0.38	**-1.76**	0.02	**2.01**	-0.18	-0.21	**1.96**	0.24
	(0.19)	(0.14)	(0.18)	(0.21)	(0.15)	(0.27)	(0.21)	(0.24)	(0.30)	(0.23)	(0.20)	(0.23)	(0.31)	(0.21)	(0.26)
Time	**0.67**	**-0.07**	**-0.49**	**0.72**	**-0.20**	**1.02**	**-0.10**	**-0.57**	**1.00**	**1.06**	**-0.08**	**-0.30**	**0.40**	-0.02	**-0.28**
	(0.11)	(0.02)	(0.08)	(0.09)	(0.02)	(0.11)	(0.03)	(0.09)	(0.11)	(0.10)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Time^2	**-0.16**	–	**0.03**	**-0.04**	–	**-0.18**	–	**0.03**	**-0.06**	**-0.19**	–	–	–	–	–
	(0.03)		(0.01)	(0.01)		(0.03)		(0.01)	(0.01)	(0.03)					
Time^3	**0.01**	–	–	–	–	**0.01**	–	–	–	**0.01**	–	–	–	–	–
	(0.00)					(0.00)				(0.00)					
Condition	–	–	–	–	–	-0.53	-0.15	0.55	-0.07	-0.13	0.13	-0.08	**-1.15**	0.12	0.53
						(0.34)	(0.28)	(0.29)	(0.37)	(0.29)	(0.28)	(0.30)	(0.41)	(0.30)	(0.34)

Table 1 (continued)

	Study 2 (N = 134)					Study 3 (N = 129)				Study 4 (N = 150)					
Random effects	RE	MO	TP	OC	VA	RE	MO	TP	OC	PRE	MO	TP	OC	MRE	IN
Between-person															
Intercept	1.72	1.13	1.74	1.96	1.23	2.07	1.22	1.69	1.75	1.85	1.52	1.61	2.33	1.46	1.62
Time	0.53	0.12	0.74	0.74	0.16	0.69	0.20	0.72	0.86	0.61	0.20	0.20	0.20	0.20	0.18
Time^2	0.00	–	0.06	0.07	–	0.05	–	0.06	0.07	0.06	–	–	–	–	–
Time^3	0.01	–	–	–	–	–	–	–	–	0.00	–	–	–	–	–
Within-person															
Residual	1.35	1.32	1.21	1.45	1.52	1.21	1.37	1.38	2.01	0.91	0.99	1.38	1.82	1.22	1.68
AR(1)	.49	.68	.50	.45	.53	.55	.60	.48	.65	.26	.32	.47	.58	.56	.60
Marginal R^2	.01	.01	.09	.14	.05	.06	.02	.14	.16	.10	.01	.08	.12	.00	.07
Conditional R^2	.74	.61	.77	.78	.63	.78	.60	.69	.65	.83	.77	.66	.66	.68	.61

Note. RE = Recovery; MO = Mood; TP = Time Perception; OC = Opportunity Costs; VA = Valence; PRE = Physical Recovery; MRE = Mental Recovery; IN = Interest. The fixed effects are reported as unstandardized regression coefficients. The random effects are reported as standard deviations and correlations. Condition is coded 0 = high opportunity costs and 1 = low opportunity costs. The fixed effects estimates in bold are significant (all ps < .001, except for the main effect of condition on opportunity costs in Study 4, with p = .006). Marginal R^2 depicts the proportion of explained variance of the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined (Nakagawa & Schielzeth, 2013; Johnson, 2014).

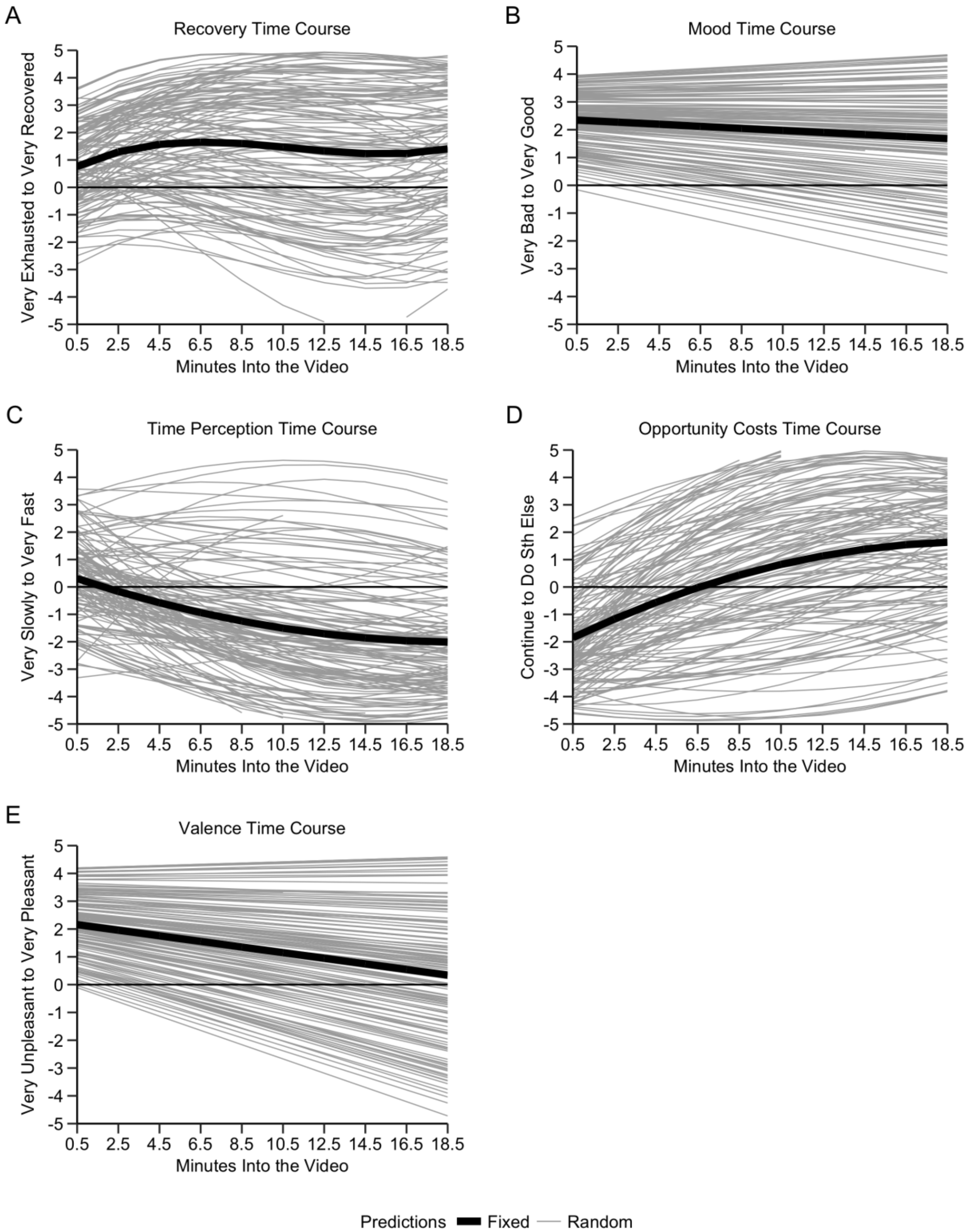

Figure 4. Spaghetti plots of the fixed and random effects of time (Study 2). Panel A: Experienced recovery, B: Mood, C: Time perception, D: Opportunity costs, E: Valence of the activity.

Random slopes correlations. The estimates of the random slopes correlations are shown in Table 2. These within-person associations provide information about the degree of association between the rate of change in one variable and the rate of change in another. Out of all the indicator variables, only the random slopes for mood showed a substantial correlation with the random slopes for recovery: Persons who reported a steeper increase (decrease) in mood during the recovery period also showed a steeper initial increase (decrease) in recovery. The random slopes for mood, activity valence, and time perception evinced a positive manifold: Persons who reported an increase (decrease) in one of those variables also reported an increase (decrease) in the other variables over time. Lastly, the random slopes for opportunity costs were negatively associated with the random slopes for activity valence and time perception: Persons who reported an increase (decrease) in opportunity costs perceived the video as less (more) pleasant and time as more (less) extending as time went on.

Brief Discussion

The central finding of Study 2 is that changes in mood were substantially associated with changes in recovery within persons. In comparison, none of the other psychological indicators covaried with the experience of recovery over time. Furthermore, we found first evidence for the hypothesized time course of experienced recovery and opportunity costs during a relaxing activity. Regarding recovery, persons tend to recover only for a limited amount of time, and report decreases in recovery when they stay engaged in a relaxing activity past a certain point. This finding suggests that relaxing activities do not contribute to the experience of recovery indefinitely. The amount of time to the point when the activity no longer contributes to one's recovery varies greatly between persons, as is evident by the substantial variation in individual slopes (see Figure 4, panel A). Hence, in a next step, we sought to explain this between-person variability in the slopes for recovery.

Table 2

Bayesian Multivariate Multilevel Growth Curve Model Estimates of the Random Slopes Correlations (Study 2).

Random Slope	1	2	3	4
1. Recovery	–			
2. Mood	**.46 [.22, .67]**	–		
3. Valence	.11 [-.15, .35]	**.49 [.23, .71]**	–	
4. Time Perception	.10 [-.13, .33]	**.37 [.13, .58]**	**.27 [.02, .50]**	–
5. Opportunity Costs	.03 [-.22, .28]	-.13 [-.39, .15]	**-.42 [-.63, -.16]**	**-.47 [-.66, -.25]**

Note. N = 134. Reported are the means of the posterior distributions (95% credible intervals in brackets). Correlations in bold are substantial (their 95% CIs do not include 0).

The average opportunity costs slope showed a strong increase as recovery progressed, which might indicate that opportunity costs are central for understanding whether an activity is experienced as relaxing or not. For this reason, in Studies 3 and 4 we manipulated perceived opportunity costs to examine whether such a manipulation can explain some of the between-person variability in the slopes for recovery.

We decided against a mood manipulation for the following reasons: First, in this study design, a manipulation of the psychological indicators of recovery needs to take place between the exhaustion and recovery period. Thus, the manipulation needs to be as quick as possible so as to not interfere with the recovery process. Because mood manipulations typically take some minutes, we did not see any viable solution on how to implement a mood manipulation in such a short amount of time. Second, even if we were successful in implementing a short mood manipulation, we still would have no way of knowing if a person attributes her or his mood on the mood manipulation activity itself or on the relaxing activity (the latter of which is what would be necessary to test a causal relationship between mood and recovery; Schwarz, 2011).

Study 3

The aims of Study 3 were to (1) replicate the results of Study 2, and (2) test for a causal relationship between opportunity costs and recovery by manipulating the perceived opportunity costs of a relaxing activity. To this end, we employed the same design as in Study 2 with a few alterations: As an easier and shorter way to induce exhaustion, we employed 5-minutes of stair running instead of the 20-minutes high intensity interval training from Study 2. Further, in a comprehensive pilot study we presented participants ($N = 296$) with a list of computer-based activities and asked them to rate the extent to which they would prefer doing these activities compared to watching a relaxing aquatic video. Results suggested that watching funny YouTube videos, online shopping, looking something up online, and mind wandering were the most attractive alternatives, while watching old weather forecasts, reading an article of a tabloid, and listening to old German pop songs were the most unattractive alternatives. As the attractive and unattractive activities had to be as comparable as possible on all other dimensions, we settled on watching funny YouTube videos as the attractive alternative and watching old weather forecasts as the unattractive alternative. Thus, in Study 3, before participants began watching the relaxing video, we told them that after the relaxing video had ended, they would either watch very funny or boring YouTube videos. With this manipulation, we sought to alter the perceived opportunity costs of the relaxing activity (i.e., induce high costs in the "funny videos" condition and induce low costs in the "boring videos" condition). Based on our theoretical considerations about psychological indicators of exhaustion and recovery (Cardini & Freund, 2019a), we hypothesized that participants in the "funny videos" or high costs condition feel recovered faster than participants in the "boring videos" or low costs condition, if experiences of increasing opportunity costs serve as an indication that a relaxing activity has fulfilled its goal of recovering a person.

Method

Participants. An a-priori power analysis with G*Power (Version 3.1; Faul et al., 2009) indicated that we needed at least 120 participants to detect an interaction of a between-person (condition: high costs vs. low costs) and within-person (time) factor with a small population effect size (Cohen's $f = 0.10$), 95% power and a 5% error probability in a repeated measures design consisting of ten measurement occasions. We applied the same inclusion criteria as in Study 2, with the addition that participants had not participated in Study 2. A total of $N = 129$ adults ($M_{age} = 28.17$ years, $SD = 9.98$; 56% female) participated in this study. Approximately two thirds of the sample consisted of students (64%). In general, participants reported relatively high physical fitness ($M = 3.47$, $SD = .95$, range from 0 [*not fit at all*] to 5 [*very fit*]).

Measures. We used the same measures as in Study 2, with two exceptions: (1) We omitted the activity valence item from the list of dependent variables, because it showed substantial correlations with the random slopes of mood, time perception, and opportunity costs in Study 2, and (2) we included the main effect of the between-person condition variable (coded 0 = high costs, 1 = low costs) as an additional independent variable.

Procedure. The procedure was identical to Study 2, with the following modifications: Instead of a 20-minute high intensity interval training, participants ran up and down the stairs of the 5-floor University building for five minutes. We instructed participants to run as quickly as possible. In order to motivate participants to exert maximal effort, either a student assistant or the first author took part in each stair running session. Afterwards, participants were immediately guided into a lab room, where they were seated in front of a computer.

Before they started watching the relaxing aquatic video, participants were randomly assigned to one of two conditions: Participants in the high costs (low costs) condition were instructed that after watching the relaxing video, they would see very funny (very boring) YouTube videos. Because we run a "no deception lab," this was actually the case.

Statistical analysis. The analysis approach was the same as in Study 2.

Results

Exhaustion manipulation check. Participants reported a significant decrease in recovery (increase in exhaustion) after the training (M = -2.33, SD = 2.27) compared to before (M = 1.25, SD = 2.33), $t(128) = 13.73$, $p < .001$, 95% CI of the mean difference [3.07, 4.10], d = 0.73, 95% CI [0.48, 0.99]. Thus, the stair running successfully induced exhaustion. In comparison, the other dependent variables did not change meaningfully on average before vs. after the training ($|d|$s between 0.05 to 0.24; see Table A2 in Appendix A).

Preliminary analyses and model building. The initial multilevel analysis dataset consisted of N = 129 participants x 10 measurement occasions = 1,290 observations. Inspection of the scatterplots, person by person, indicated that due to a very infrequent technical failure, three persons had missing data between six and nine measurement occasions. Thus, the final analysis dataset consisted of 1,267 observations. The scatterplots further revealed that eight participants reported a ceiling effect of recovery without any substantial changes for the ten measurement time points. However, these participants did report changes in other dependent variables, therefore we refrained from excluding them from the analyses. The model building process was the same as in Study 2.

Opportunity costs manipulation check. To check whether the opportunity costs manipulation had worked, we inspected the opportunity costs time course for both conditions. Contrary to our expectations based on the pilot study, the main effect of condition was not significant, b = 0.07, $t(127) = -0.18$, p = .85, 95% CI [-0.80, 0.67]. Thus, the experimental manipulation was not successful.[1] For further analyses, we collapsed the two experimental conditions and proceeded with the analyses in a correlational manner just as in Study 2.

Time courses and random slopes correlations. As can be seen in Table 1, the time courses of the dependent variables were very similar to the ones found in Study 2. Further, we also replicated the correlations of the random slopes found in Study 2 (see Table A4 in Appendix A), with one exception: In this study, the random slopes of mood were substantially negatively correlated with the random slopes of perceived opportunity costs: Persons who experienced a steeper decline (increase) in mood also experienced a steeper increase (decline) in opportunity costs throughout the recovery period. Again, changes in mood were significantly related to changes in recovery over time, whereas all other indicators were not. This replicates the main result of Study 2.

Brief Discussion

This study replicated the pattern of results of Study 2 regarding the time courses of the dependent variables and their random slopes correlations. Again, changes in mood were significantly related to changes in recovery within person, and none of the other

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[1] Although the manipulation check indicated that we were not successful in manipulating the opportunity costs with our procedure, we tested if the two groups differed in their recovery. Table 1 shows the main effect of the between-person condition variable (coded 0 = high costs, 1 = low costs) on the within-person time variable (coded 0 to 9) for the dependent variables. Of particular interest is the main effect of condition for the recovery variable. Our main hypothesis for this study was that persons in the high costs condition feel recovered faster than persons in the low costs condition. However, regarding recovery, the main effect term was not significant, $b = -0.53$, $t(127) = -1.59$, $p = .11$, 95% CI [-1.20, 0.13]. Thus, participants in both conditions did not differ in their recovery time courses.

psychological indicators of recovery included in this study covaried significantly with recovery.

Despite the extensive pilot study, we were not successful in experimentally manipulating opportunity costs in Study 3. Thus, we were unable to test the hypothesis that perceived opportunity costs might underlie the experience of recovery. For Study 4, we conducted more pilot studies on the experimental induction of high vs. low opportunity costs and re-ran Study 3.

Study 4

Aiming at identifying a reliable way to experimentally induce high vs. low opportunity costs, we piloted three different manipulations: (1) the same instruction manipulation as in Study 3 but with additional preview clips of the attractive or unattractive alternatives, (2) making a donation to charitable institutions as the attractive alternative and performing a mindless task (repetitive clicking on a set of words; Markey, Chin, VanEpps, & Loewenstein, 2014) as the unattractive alternative, and (3) having participants think about what attractive or unattractive activity they could be doing instead of taking part in the experiment and keeping this activity salient throughout the recovery period. Results of the pilot studies suggested that the third approach was most effective in altering participant's perceived opportunity costs right before, during, and after the recovery period. Therefore, we adopted this manipulation paradigm in Study 4.

In Studies 2 and 3, a small subset of participants reported higher levels of recovery after the exhaustion period compared to before. We suspected that these participants might have weighted their cognitive activation following the physical exercise more strongly towards their assessment of recovery than their feelings of physical exertion. Therefore, in Study 4 we included a distinction between physical and mental recovery and exhaustion with the aim of achieving a more homogenous assessment of these constructs. Furthermore, some of the participants in Studies 2 and 3 anecdotally gave us the feedback that they became bored after watching the relaxing video for a while. To be able to disentangle boredom from recovery, we also included a measure of boredom.

Method

Participants. An a-priori Monte Carlo power analysis (Green & MacLeod, 2016) using simulated data from the third pilot study revealed that we needed 150 participants to detect a main effect of condition on the opportunity costs time course with 95% power and a 5% error probability. The study had the same inclusion criteria as Studies 2 and 3 with the addition that participants had not participated in the previous main and pilot studies. A total of $N = 150$ participants ($M_{\text{age}} = 28.09$ years, $SD = 12.23$; 71% female) of mostly students (71%) participated in this study. As in the previous studies, participants reported relatively high physical fitness ($M = 3.17$, $SD = .97$, range from 0 [*not fit at all*] to 5 [*very fit*]).

Measures. We used the same dependent variables as in Study 3, with the following additions: (1) We assessed recovery with the two items "*How do you feel right now physically*?" and "*How do you feel right now mentally*?" and (2) we included the interest/boredom item "*How do you perceive this activity right now?*" with -5 (*very boring*) and +5 (*very interesting*) as verbal anchors.

We also included a number of additional opportunity costs manipulation checks: Right after the manipulation and before the relaxing video started, participants indicated the degree to which they wanted to watch the relaxing video versus engage in the alternative activity with the item "*Which of these activities would you rather do right now?*" with -5 (*do the alternative activity*) and +5 (*watch the relaxing video*) as verbal anchors. Immediately after the relaxing video had ended, we asked participants to guess how long the video had lasted and to indicate how long the video ideally should have lasted for them to fully recover. Further, we asked participants to indicate how often they had thought of the alternative activity while watching the video on a scale of 0 (*not at all*) to 5 (*a lot*) and how attractive the alternative activity was compared to watching the video on a scale of -5 (*a lot more unattractive*) to +5 (*a lot more attractive*).

Procedure. The procedure was identical to Study 3, with the following modifications: For the opportunity costs manipulation, we asked participants to think of an attractive (high costs condition) or unattractive (low costs condition) alternative activity that they could be doing instead of participating in the study. We then kept this activity salient throughout the recovery period by briefly reminding participants of this activity at each measurement occasion before they answered the questions.

Statistical analysis. The data analytical procedure was the same as in Studies 2 and 3.

Results

Exhaustion manipulation check. Participants reported a significant increase in *physical* exhaustion after the training ($M = -1.49$, $SD = 2.12$) compared to before ($M = 0.96$, $SD = 1.94$), $t(149) = 11.02$, $p < .001$, 95% CI of the mean difference [2.01, 2.89], $d = 0.89$, 95% CI [0.66, 1.13]. Thus, as in Study 3, the stair running was successful in inducing physical exhaustion. In contrast, participants reported feeling slightly more *mentally* recovered after the training ($M = 1.79$, $SD = 1.82$) compared to before ($M = 1.36$, $SD = 1.79$), $t(149) = -2.25$, $p = .03$, 95% CI of the mean difference [-0.81, -0.05], $d = -0.14$, 95% CI [-0.37, 0.08]. As in the previous two studies, the other dependent variables did on average not change meaningfully before vs. after the training ($|d|$s between 0.03 to 0.27; see Table A3 in Appendix A).

Preliminary analyses and model building. The initial multilevel analysis dataset consisted of $N = 150$ participants x 8 measurement occasions = 1,200 observations. There were no missing data. Inspection of the person-by-person scatterplots revealed that two participants reported a ceiling effect of recovery without any substantial changes for the eight measurement time points. However, as in the previous two studies, these participants reported changes in other dependent variables, therefore we refrained from excluding them from the analyses. The model building process was the same as in Studies 2 and 3.

Time courses and random slopes correlations. As can be seen in Table 1, the time courses of the dependent variables were very similar to the ones found in Studies 2 and 3. Mental recovery was the only dependent variable that did not change meaningfully over time on average. The time course of interest/boredom was similar to the one of time perception: Both started out near the neutral zero point and decreased as time went on (i.e., time started to extend and boredom to increase). We also replicated the random slopes correlations found in the previous two studies (see Table A5 in Appendix A), with one exception: As in Study 2 and unlike Study 3, the random slopes of mood were not correlated with the random slopes of opportunity costs. The random slopes of mental recovery were positively associated with the random slopes of physical recovery, mood, and interest, and negatively with the random slopes of opportunity costs. The random slopes of interest/boredom were positively associated with the random slopes of mental recovery, mood, and time perception, and negatively with the random slopes of opportunity costs.

Opportunity costs manipulation checks. Regarding the opportunity costs manipulation check, we found a significant main effect of condition on opportunity costs, b = -1.15, $t(148) = -2.82$, $p = .006$, 95% CI [-1.95, -0.34], with a substantial effect size (semi-partial marginal $R^2 = .04$, 95% CI [.06, .02]; Nakagawa & Schielzeth, 2013; Johnson, 2014). As the model with only the main effects of time and condition (AIC = 4712.4, BIC = 4753.1) fitted the data better than the model with an additional time and condition interaction term (AIC = 4714.1, BIC = 4759.9), we conclude that, although opportunity costs increased for both conditions as time went on, they were on average 1.15 units lower for the low costs condition throughout the whole recovery period.

Regarding the pre-video manipulation-check item, the high costs condition reported substantially lower scores (M = -1.36, SD = 3.15) compared to the low costs condition (M = 3.19, SD = 2.42), t(132.94) = -9.87, p < .001, 95% CI of the mean difference [-5.46, -3.64], d = 1.61, 95% CI [1.24, 1.98]; note that the scale of this item ranged from -5 (*do the alternative activity*) to +5 (*watch the relaxing video*). Thus, as expected, participants in the high costs condition reported rather wanting to do the alternative activity, while participants in the low costs condition reported rather wanting to watch the relaxing video. In addition, participants in the high costs condition reported a higher frequency of thoughts about the alternative activity while watching the video (M = 2.36, SD = 1.37) compared to those in the low costs condition (M = 1.69, SD = 1.48), t(146.98) = 2.88, p = .005, 95% CI of the mean difference [0.21, 1.13], d = -0.47, 95% CI [-0.80, -0.14], and found the alternative activity more attractive (M = 3.57, SD = 1.18) than those in the low costs condition (M = 1.90, SD = 1.49), t(143.30) = 7.61, p < .001, 95% CI of the mean difference [1.24, 2.11], d = -1.25, 95% CI [-1.60, -0.89].

Main hypothesis test. To test the hypothesis that participants in the high costs condition feel recovered faster than participants in the low costs condition, we analyzed the main effect of condition on time with physical recovery as the dependent variable. Contrary to our expectation, this term was not significant, b = -0.13, t(148) = -0.45, p = .66, 95% CI [-0.70, 0.44]: Participants in both conditions did not differ in their recovery time courses.

Brief Discussion

Although we were successful in manipulating opportunity costs before, during, and after a recovery period in Study 4, we did not find evidence for the hypothesis that persons with high opportunity costs feel recovered faster than persons with low opportunity costs. Considering these results, along with the descriptive results of Study 1 and the correlative findings of Studies 2 and 3, the evidence against the hypothesis that perceived opportunity costs of a relaxing activity influence feelings of physical recovery is strong and suggests that it should be rejected. In contrast, replicating the pattern of results from Studies 2 and 3, the correlative findings of Study 4 suggest again that changes in mood are related to changes in the experienced recovery within person.

General Discussion

What indicates short-term recovery? Across four studies, we examined the role of opportunity costs, mood, and subjective time perception as indicators of subjective recovery. We consistently found a positive relationship between mood and subjective recovery: People's lay beliefs revealed that "feeling good" is the most salient cue for assessing their recovery progress (Study 1). This link was further corroborated experimentally: Following an exhaustion induction, participants' subjective recovery over time and changes in their mood were positively correlated within persons (Studies 2-4). In contrast, we did not find strong support for the theorized link between opportunity costs and recovery, and found no support for the relationship between subjective time perception and recovery. Nevertheless, on the basis of theoretical considerations (cf. Kurzban et al., 2013) and the finding in Study 2 that perceived opportunity costs sharply increased over the course of the recovery period, we targeted this construct for experimental manipulation that we successfully achieved in Study 4. However, we found no evidence for the hypothesis that perceiving high opportunity costs during a recovery period accelerates the speed of subjective recovery.

Positioning Mood as an Indicator of Recovery

The findings of the present studies are in line with conceptualizations of recovery as a process of "repairing" one's mood (Sonnentag & Fritz, 2007; Thayer, 1989; Watson, Clark, & Tellegen, 1988). For instance, in his biopsychological mood model, Thayer (1989) describes mood as arising from the interplay between the degree of energy (vs. tiredness) and tension (vs. calmness) that is presently experienced by a person. According to Thayer, the optimal mood state is comprised of high levels of energy and low levels of tension (i.e., calm energy; Thayer, 2001), whereas a particularly negative mood state is comprised of low levels of energy and high levels of tension. Similarly, in their circumplex model of affect, Watson et al. (1988) describe positive affect as a state of high energy, full concentration, and pleasurable engagement, whereas negative affect is comprised of subjective distress, unpleasurable engagement, and a variety of negative emotions. Our research adds to these conceptualizations by positioning mood as an indicator of recovery.

Prior empirical evidence for the relationship between mood and recovery has been scarce. For example, Sonnentag and Zijlstra (2006) found that people who reported a higher need for recovery after a working day also tended to report a worse mood at bedtime. Further, Sonnentag, Binnewies, and Mojza (2008) found that evening recovery experiences (i.e., psychological detachment from work, relaxation, mastery, and control; Sonnentag & Fritz, 2007) positively predicted mood the next morning. However, a limitation of the two studies by Sonnentag and colleagues (Sonnentag & Zijlstra, 2006; Sonnentag et al., 2008) is that they did not assess the degree of subjective recovery but used proximate constructs such as need for recovery or experiences during the recovery process. Moreover, there was a temporal gap between the assessment of mood and recovery, thus telling us little about the co-occurrence of both variables.

To our knowledge, this paper presents the first set of studies that have found a positive *concurrent* association between mood and subjective recovery. We hasten to add, however, that we do not view recovery as merely reflecting one’s current mood state. In our view, mood and recovery are conceptually related, yet not conterminous constructs (Cardini & Freund, 2019a). In particular, we conceptualize *changes* in mood as an indication of recovery, in that mood is only positively related to recovery for as long as the current activity contributes to one’s recovery, and that mood starts to decline once recovery is achieved, as a motivational cue for goal disengagement. However, we acknowledge that the current studies cannot directly address this second part of our assumption (i.e., that mood starts to decline once recovery is achieved).

What Do Perceived Opportunity Costs Reflect?

Contrary to our expectation, we did not find strong support for the theorized association between opportunity costs and recovery. Specifically, instructing people to think about an attractive or unattractive alternative activity did not seem to have an effect on their subjective recovery from physical exertion. It seems that people do not use the attractiveness of or the thought frequency about alternative activities as a cue for evaluating their recovery progress. This finding contradicts our hypothesis that experiencing opportunity costs signals that the present activity has fulfilled its goal of recovery and should be discontinued (Cardini & Freund, 2019a).

However, in partial support of our hypothesis, Study 4 revealed that persons who reported an increase in opportunity costs also tended to report a decrease in mental recovery (increase in mental exhaustion) during the recovery period. Perhaps, then, opportunity costs are more relevant for exhaustion. This view is supported by Kurzban et al. (2013), who propose that an activity's opportunity costs are experienced as mental effort: The higher an activity's opportunity costs, the more mentally demanding an activity is perceived. Thus, instead of signaling goal disengagement, opportunity costs might instead function as an input for experienced effort. This is further corroborated by the findings of Studies 2, 3, and 4 that opportunity costs increase somewhat as a result of demanding exercise (see Tables A1-A3 in Appendix A).

Subjective Recovery Is a Domain-Specific Construct

Study 4 showed that participants on average reported a slight increase in *mental* recovery after demanding physical exercise despite feeling substantially more *physically* exhausted. Study 4 also showed that participants did not report mean changes in mental recovery during the recovery period, despite reporting mean changes in physical recovery. This suggests that physical and mental recovery, while positively correlated (see Table A5 in Appendix A) are dissociable constructs that are characterized by differential time courses and affected by different factors. For instance, Study 4 showed that mental, but not physical recovery was associated with opportunity costs and interest: People who reported higher mental recovery also reported lower opportunity costs and higher interest in the relaxing activity. It might be that certain motivational variables such as interest and opportunity costs affect mental recovery more than physical recovery.

This finding is in line with previous research showing that acute physical exercise can have a beneficial effect on the performance of subsequent cognitive tasks (Brisswalter et al., 2002; Lambourne & Tomporowski, 2010). One explanation of this finding is that physical exercise leads to an increase in physiological arousal, which in turn facilitates cognitive functioning (Tomporowski, 2003; Audiffren, 2009).

Limitations and Future Directions

This set of studies has some limitations. First, in their meta-analysis on the effect of acute physical exercise on cognition, Lambourne and Tomporowski (2010, p. 17) conclude that “typical laboratory-based exercise protocols that are presumed to produce fatigue may be insufficient to simulate the physiological demands encountered in naturalistic sport and extreme human performance environments.” Furthermore, although our choice of the aquatic video was based on empirical work (Piferi et al., 2000) demonstrating that the video induced a faster physiological recovery from a period of effortful activity compared to traditional resting, this relaxing activity might not have been as effective at impacting the subjective experience of recovery, as was evident by the relatively small fixed effects of recovery in Studies 2-4 and the gradual increase of boredom in Study 4. Thus, the physical exercises and recovery activity might not have fully induced the extent of exhaustion and recovery one might expect to find in naturalistic settings.

Second, the very fact that persons likely planned their schedule so as to include participation in the study might have lessened their experiences of opportunity costs during the experiments: Knowing that the experiment lasted only for about an hour and planning accordingly might have lowered the perceived opportunity costs. For instance, while persons in the high opportunity costs condition in Study 4 rated alternative activities as more attractive (and persons in the low opportunity costs condition rated alternative activities as more unattractive) compared to watching the relaxing video, the knowledge that the relaxing video had a fixed endpoint determined by the experiment might have counteracted the value of these alternative activities. Opportunity costs might be more pressing when people can realistically envision doing something better with their time.

Third, we did not capture the exact point in time where participants felt sufficiently recovered and wanted to disengage from the relaxing activity (i.e., goal attainment). Instead, we inferred this information from the subjective recovery and opportunity costs time courses. Assessing these constructs with a lag of two minutes during the recovery period might have been too coarse to detect interindividual differences in this regard. However, even assessing these variables every two minutes seemed pushing the feasibility of the frequency with which we interrupted their recovery experience. Alternatively, we could have introduced a stopping rule and asked participants to stop when they no longer enjoy the task or when they feel sufficiently recovered. Previous research suggests that people in a negative mood disengage faster from the task than people in a positive mood, given that mood reflects one's task enjoyment (Martin et al., 1993).

Lastly, one might argue that mood and recovery are confounded in the methodology, because the relaxing video might have induced both positive mood and recovery independent of each other. In other words, the video in itself might be a positive mood manipulation that participants happen to watch while they are also recovering from physical exertion. In this case, the positive association between mood and recovery might be spurious due to the video as a confounding variable. However, in one of the pilot studies conducted for Study 4, we had young adults (N = 20) watch the relaxing video without inducing exhaustion beforehand. In this scenario, mood remained stable within- and between-person for the whole video duration (fixed effect of time: b = 0.01, SE = 0.04, 95% CI [-0.08, 0.10]; random-intercept-and-slope model did not provide better model fit compared to random-intercept-only model, p = .28). Thus, it appears that the video does not necessarily in itself induce positive mood. It seems more likely, then, that the increase in positive mood during the video in our studies is primarily due to participant's recovery from induced exhaustion.

Keeping these limitations in mind, we suggest that future work should consider assessing exhaustion and recovery in everyday life. Advantages to such an approach include: (1) We would learn how exhaustion and recovery unfold in a natural setting, where (2) people can freely choose their preferred exhausting and relaxing activities, and where we can (3) measure the same people across many exhausting and relaxing activities to get a more reliable estimate of the exhaustion and recovery time courses along with their proposed indicators. In addition, laboratory studies building on the design of the current studies could complement the field studies in a more controlled environment.

Conclusions

How do we know when an activity has helped us recover, and when it is time to disengage from it in order to pursue more beneficial alternatives? Across four methodologically diverse studies encompassing qualitative, correlational, and experimental designs, we consistently found evidence for a positive within-person association between changes in mood and recovery: When people recover, they simultaneously elevate their mood. This relationship was not present at the between-person level: Average mood consistently showed a slight linear decrease during the recovery period. Thus, the relationship between mood and recovery might not be as straightforward as previously assumed (e.g., Sonnentag & Fritz, 2007). In contrast, it seems that people do not take their perceived opportunity costs and subjective sense of time as an indication of their recovery. However, people might nevertheless take their perceived opportunity costs as an indication of effort and, by extension, exhaustion. In fact, to our knowledge, this set of studies provides first empirical evidence for the core assumption underlying Kurzban et al.'s (2013) opportunity cost model of subjective effort. Taken together, then, the present research contributes two novel insights to our understanding of emotion and motivation: (1) Changes in mood might be an indicator of recovery, and (2) perceived opportunity costs might be one of the psychological inputs people use to determine their physical and mental states of exhaustion and might play an important role in the process of goal disengagement (see also Hofmann et al., 2019).

These results have implications for other areas of research. For instance, Sonnentag and Fritz (2007) have stressed the importance of psychological detachment, relaxation, mastery, and control for recovery from work-related stress. Furthermore, Newman, Tay, and Diener (2014) have singled out experiences of detachment, autonomy, mastery, meaning, and affiliation for promoting subjective well-being during leisure. Our results suggest that strategies aimed at improving one's mood (e.g., listening to music; Thayer et al., 1994) represent another important avenue for promoting recovery.

PART III: MORE OR LESS ENERGY WITH AGE? A MOTIVATIONAL LIFE-SPAN PERSPECTIVE ON ENERGY, EXHAUSTION, AND OPPORTUNITY COSTS

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This article has been submitted for publication (2019) in a peer-reviewed journal and is currently under review. Please do not copy or cite without permission of the authors.

Abstract

Two studies investigated subjective conceptualizations of energy for goal pursuit across adulthood. Study 1 (*N* = 276, 20-92 years) explored age-related differences in the (a) endorsement of a limited vs. nonlimited account of energy for goal pursuit, (b) amount of energy available for physically, mentally, socially, and emotionally demanding activities, and (c) extent to which spending energy on a demanding activity inhibits or facilitates energy expenditure for subsequent activities, both within and across functional domains. Study 2 (*N* = 147, 18-86 years) experimentally induced energy loss through a 20-minute physical exercise and examined age-related differences in the increase of subjective exhaustion and opportunity costs as a motivational cue for goal disengagement. With increasing age, adults more strongly endorsed a nonlimited account of energy and perceived to have more energy available for personally relevant mental and social activities. However, older adults also reported higher negative cross-domain energy spillover after physical exertion. Multilevel growth curve models further revealed that, compared to younger adults, older adults reported a steeper initial increase in exhaustion and opportunity costs during physical exercise, but converged with the younger age groups again at the close of the exercise session. The discussion centers around the importance of selectivity in older adulthood and motivational accounts of effort and exhaustion.

Introduction

Energy fuels many of our goal pursuits. For instance, maintaining fitness requires engaging in regular physical exercise. Writing a manuscript necessitates intense thinking about how to efficiently translate abstract ideas into engaging scientific prose. Cultivating a valued friendship requires emotional involvement and "being there" during tough times. Indeed, energy seems instrumental to achieve all of these desired ends. Yet, despite the apparent ubiquity of energy-consuming activities, surprisingly little is known about the nature of energy and its changes across adulthood. In the present studies, we addressed this research gap by examining how people conceive of energy, whether they differentiate between kinds of energy (e.g., energy for physical exercise, for mental activity, for emotional involvement), and how the subjective availability of energy might change across adulthood.

To preview, in Study 1 we examined age-related differences in (1) the endorsement of a limited vs. nonlimited account of energy for goal pursuit, similar to, but distinct from, subjective beliefs about willpower (Job et al., 2010) or the malleability of abilities (Dweck, 2008), (2) the perceived amount of available energy for everyday activities in different functional domains (physical, mental, social, emotional), and (3) the extent to which people believe that spending energy on a demanding activity in a given functional domain affects their available energy for subsequent activities (i.e., energy spillover). In Study 2, we expanded on some of the key results of Study 1. In particular, we experimentally induced a state of energy loss due to physical exertion and examined age-related differences in proximal motivational consequences, such as subjective *exhaustion* and *opportunity costs* (i.e., the extent to which one would rather spend currently available energy on attractive alternatives; Kurzban et al., 2013).

In what follows, we first provide a working definition of energy. Next, we outline possible age-related differences in the subjective availability of energy in different functional domains. Finally, we take a motivational perspective on energy and derive age-differential hypotheses about the development of subjective exhaustion and opportunity costs during effortful activities.

Toward a Working Definition of Energy

Energy is a broad concept that is used in many different scientific fields. The most basic definition of energy stems from physics, where it refers to “the capacity for doing work” (Merriam-Webster, 2019). Work is the action of moving something against a force. Energy, in physics, is bound to the first law of thermodynamics: It can be neither created nor destroyed but only converted from one form to another. The same principle of energy applies to biology: Living organisms require energy to do the work necessary for survival and reproduction. In the case of humans and other omnivores, this energy is generated from the nutrients in their food through the process of aerobic cellular respiration. In short, inhaled oxygen breaks down the ingested nutrients (e.g., glucose) in a set of chemical reactions, thereby releasing chemical energy, which is converted into mechanical energy, for instance to produce work in the form of muscle contractions. The expenditure of such energy can be measured reliably in units of joules.

In stark contrast, energy is a surprisingly elusive construct in psychology, despite the many ways it is used in everyday language: People *spend* energy on various activities, *waste* energy on boring ones, *save* energy for later, *feel* energetic or drained, and need to *recharge* energy after a long day at work. To what kind of energy do people refer in these instances? In our view, people's everyday usage of energy taps into three different aspects of experience and behavior: (i) the *subjective availability of energy* or the perceived potential to perform a task (e.g., “I don’t have the energy to do the laundry right now”), (ii) the actual *process of spending energy* or the execution of physical and/or mental operations in the service of progressing on a task (e.g., “I’m wasting my energy on these chores”), and (iii) the *phenomenology of spending energy* or the sense of effort and exhaustion associated with sustained physical and/or mental activity (e.g., "Interacting with this person feels strenuous and is draining my energy"). For the sake of clarity, we restrict our working definition of energy to the first aspect: the perceived potential to perform a task or pursue a goal.

How is this working definition of energy different from related constructs such as willpower and effort? *Willpower* or self-control is a volitional construct that denotes people's willingness to initiate and maintain goal-relevant behavior in the face of setbacks, obstacles, or temptations (e.g., the extent to which a person is willing to resist the desire to lazily lounge on the sofa and, instead, go on the planned hike in the Alpes; Inzlicht & Schmeichel, 2012; Job et al., 2010; Muraven & Baumeister, 2000). In contrast, we maintain that *energy* is a broader construct that denotes people's perceived potential to perform a task or to pursue a goal (e.g., the extent to which the person perceives herself capable to do the 6-hour hike). *Effort*, in turn, refers to the perceived amount of energy people invest into a task or goal at hand (e.g., the amount of physical and/or mental labor the person experiences while hiking; Inzlicht et al., 2018; Kurzban, 2016). Effort can be conceptualized as "the process that mediates between how well an organism can potentially perform on some task [energy] and how well they actually perform on that task [performance]" (Inzlicht et al., 2018, p. 338).

Energy, effort, and willpower are interrelated, yet refer to different motivational phenomena. For instance, a person might perceive to have sufficient energy available to run a marathon but might not be motivated to invest the required effort and thus perform poorly, or might not be willing to resist the urge of disengaging from running at the onset of muscle soreness. Conversely, a person might feel exhausted yet still be motivated to maintain effort despite the physical pain. Taken together, then, energy captures the perceived potential to perform, effort the perceived amount of invested energy, and willpower the willingness to muster the energy and effort in the service of a given goal. In motivational terms, energy can be conceptualized as a resource that *guides* goal pursuit; that is, one selects or disengages from goals based on the perceived potential to pursue them. Effort denotes a resource that *fuels* goal pursuit; that is, one mobilizes physical and/or mental activity to make progress on the selected goals (e.g., Freund, Hennecke, & Mustafić, 2012). Willpower denotes a resource that *shields* one's goal pursuit from tempting alternatives.

Age-Related Differences in Subjective Energy Availability

There are several reasons to expect age-related changes in the subjective availability of energy for goal pursuit. As people grow older, declines in physical and cognitive functioning become more prevalent (Baltes et al., 2006; Baltes & Smith, 2003). As a result, older adults become more selective in their goal pursuits (Freund & Baltes, 1998; 2002), and are more likely to avoid activities that lead to high levels of physiological arousal (Charles, 2010; Charles & Luong, 2013; Labouvie-Vief, Grühn, & Studer, 2010), or that involve high levels of mental effort (Hess, 2014; Hess, Smith, & Sharifian, 2016). Furthermore, older adults spend more time of their days in a sedentary way (Harvey, Chastin, & Skelton, 2015; Wullems, Verschueren, Degens, Morse, & Onambélé, 2016) and less time being physically active (Bauman, Merom, Bull, Buchner, & Fiatarone Singh, 2016; Sparling, Howard, Dunstan, & Owen, 2015; Sun, Norman, & While, 2013). One of the reasons for this activity/inactivity pattern might be that older adults perceive themselves to have generally *less* energy.

At the same time, however, older adulthood is characterized by a marked increase in autonomy, that is, post retirement older adults possess more freedom to decide how to structure their days and which activities and goals they want to pursue (Erikson, 1963; Ryff, 1995; Sheldon & Kasser, 2001). Given that older adults tend to avoid activities requiring high amounts of effort (Hess, 2014) and select and invest into their goals based on their available resources (Ebner et al., 2006; Freund, 2008), they might choose to engage primarily in physical and mental activities that are not very exhausting. In other words, older adults might – by selecting activities that match their perceived resources – manage their lives in a way for which they perceive to have sufficient energy. Consequently, older adults might perceive to have *similar* amounts of energy available to pursue their personal goals.

Indeed, research on subjective beliefs about developmental trajectories shows that older adults do not believe that all goal-relevant resources decline with age (Mustafić & Freund, 2012b). One example is the general-purpose resource of willpower: Job, Sieber, Rothermund, and Nikitin (2018) found that with age people are more likely to believe that willpower (i.e., the capacity to exert self-control) is *nonlimited*. In turn, endorsing a nonlimited view of willpower is associated with higher subjective well-being (Bernecker, Herrmann, Brandstätter, & Job, 2017). Job et al. (2018) demonstrated that *perceived autonomy* on demanding tasks is the mechanism driving the age-related change in self-control beliefs. This finding is in line with the proposition by Ryan and Deci (2008), that activities can maintain or even enhance one's subjective energy if they contribute to one's sense of autonomy, competence, or relatedness (see also Hope, Milyavskaya, Holding, & Koestner, 2016; Sieber, Flückiger, Mata, Bernecker, & Job, 2019).

Furthermore, with increasing age, people’s future time horizons shrink, leading to a fundamental restructuring of their goal hierarchies across various life domains, such that they tend to show a preference for present-oriented emotional goals over future-oriented goals (Carstensen, 2006; Carstensen et al., 1999). Accordingly, older adults are more likely to terminate social relationships that are emotionally unsatisfying, but maintain intensive relations with emotionally close interaction partners (Fung, Carstensen, & Lang, 2001). As a result of this “social pruning,” older adults are more satisfied with and report fewer conflicts in their remaining social relationships (Antonucci, Fiori, Birditt, & Jackey, 2010; Luong, Charles, & Fingerman, 2011). Given the importance of positive social relationships and a sense of belonging for subjective well-being and health (Nikitin & Freund, 2018; Ryff, 1995), older adults might even perceive to have *more* energy to pursue their personal goals.

Age-Related Differences in Subjective Exhaustion and Opportunity Costs

Given their motivation to maintain their current level of functioning and avoid further losses (Freund, 2006; Freund & Baltes, 1998, 2002; Freund et al., 2012), older adults might feel more driven to protect their remaining resources (e.g., energy) from superfluous goal pursuits. This assumption is supported by evidence showing that compared to younger adults, older adults report to disengage more readily from excessively costly or unattainable goals (Wrosch et al., 2003). This is adaptive, because a timely disengagement from costly yet unattainable goals helps protect older adults from developing depressive symptoms (Dunne, Wrosch, & Miller, 2011). Furthermore, compared to younger adults, older adults prioritize more efficiently between conflicting goals (Freund & Tomasik, 2019). In turn, focusing on the most important goals is related to more mutual facilitation among personal goals and to higher goal engagement (Riediger et al., 2005).

How do people determine when an activity or goal has become too costly? One potential explanation comes from recent models of exhaustion, which emphasize the importance of weighing subjective costs and benefits for goal disengagement (e.g., Boksem & Tops, 2008; Cardini & Freund, 2019a; Hockey, 2013; Inzlicht et al., 2014; Kurzban et al., 2013). For instance, Kurzban et al. have stressed the role of perceived opportunity costs as a motivational cue for goal disengagement. In short, perceiving an increase in opportunity costs during an ongoing activity leads to an increase in the sense of effort and to a decrease in the perceived utility of the activity, which in turn leads to goal disengagement (Hofmann et al., 2019). Embedding this notion into a life-span developmental context, we (Cardini & Freund, 2019a) have argued that it is adaptive for older adults to more readily detect such increases in opportunity costs, so that they can disengage earlier from activities requiring excessive amounts of energy and reengage in more beneficial activities to maintain their level of functioning and prevent further losses.

The Present Studies

Based on the research reviewed above, the present studies examined age-related differences in the subjective availability of energy for goal pursuits related to different functional domains (for the importance of assessing views on aging in a domain-specific way, see Kornadt & Rothermund, 2015). Notably, this paper merges two different empirical approaches: Study 1 explored subjective beliefs regarding the availability of energy in different age groups in a large self-report study. Study 2 was a lab-based experiment inducing the experience of having less energy available through demanding physical exercise and investigated age-related differences in the resulting proximal motivational consequences.

In Study 1, we explicitly asked people about their available energy for physically, mentally, socially, and emotionally demanding activities, and to what degree they believe that energy spent on an activity related to one functional domain facilitates or hinders their subsequent involvement in activities of other functional domains. Study 2 focused on the physical and mental domain, and inferred information related to energy expenditure indirectly through feelings of physical and mental exhaustion (e.g., Boksem & Tops, 2008) and opportunity costs (Kurzban et al., 2013). Study 2 was part of a larger experiment designed to examine age-related differences in the psychological indicators of exhaustion and recovery (Cardini & Freund, 2019a). Particularly relevant to this paper is the proposition that perceived increases in opportunity costs indicate exhaustion and serve as a motivational cue for disengagement from the exhausting activity (Cardini & Freund, 2019a). Taken together, these studies aim at providing more insight into people's beliefs (Study 1) and experiences (Study 2) governing the allocation of energy for goal pursuit across adulthood.

Study 1

Study 1 explored age-related differences in the subjective availability of energy in general and for different functional domains in particular. Based on the work outlined above, we hypothesized that older adults report to have less energy available for physically and mentally demanding activities in general, but comparable (or more) energy for self-selected physically and mentally demanding activities in which they typically engage in their everyday lives. This should be the case because we assume that older adults select activities in their everyday lives that match their level of available resources. Furthermore, we explored the possibility that older adults have more energy available for socially and emotionally demanding activities.

The study design presented us with a set of challenges. Because older adults are more selective in their goal pursuits (Freund, 2008), it was important to distinguish between available energy for activities in general and for activities that are representative of a person's everyday life (and thus personally relevant). For instance, an older adult might believe that running a marathon is nearly impossible due to physical limitations, but that climbing the stairs of the apartment building is appropriately demanding for the amount of energy they feel they have at their disposal. Furthermore, to ensure comparability of the energy ratings across age groups, we included a frame of reference to which participants could compare their currently available energy. In particular, we asked participants to relate their currently available energy to the maximum amount of energy they believe to have possessed (if the peak lies in the past), should possess currently (if it lies in the present), or will possess (if it lies in the future). Furthermore, we took great care (1) not to restrict the age group of younger adults to a homogenized student sample, and (2) to include a sample of middle-aged adults, to avoid problems associated with extreme-group comparisons (Freund & Isaacowitz, 2013).

Method

The research reported in this manuscript adhered to the guidelines of the local ethics committee, including the signing of an informed consent form and the administering of a debriefing. We report all measures of interest, exclusions, and statistical analyses in the main text.

Participants. We determined the sample size based on a-priori power analysis with the pwr-package in R (Champely, 2018), which revealed a minimum sample size of 84 participants per age group ($N = 252$) to detect a medium effect of interest ($f = .25$) with $\alpha = .05$ and 95% power. We further based our sample size estimation on Schönbrodt and Perugini (2013), who suggest a minimum of 250 participants to detect stable correlation estimates. Our only inclusion criterion was that participants had to be between 18 and 100 years old.

Initially, 426 participants were recruited from two participant pools of the Department of Psychology and the Life-Management lab of the University of Zurich (Switzerland) and gave their informed consent to participate. Of those, 334 persons completed the sociodemographic questionnaire, 279 answered the main variables of interest pertaining to subjective energy availability, and 276 filled out the dispositional measures, resulting in a final sample of $N = 276$ participants who completed the study and who were included in the statistical analyses. Of those, $n = 92$ were younger (20-35 years; 54% women), $n = 92$ middle-aged (36-64 years; 54% women), and $n = 92$ older adults (65-92 years; 54% women). As reimbursement, we raffled 10 Amazon vouchers worth 30 Swiss francs among participants. In addition, participants received a descriptive overview of the results. Dispositional sample characteristics are reported in Table 3.

Measures. The means, standard deviations, and zero-order correlations of the study variables are depicted in Tables 3-5. All items reported in this study were either translated or created in German.

Lay beliefs about energy. We included an adapted version of the 6-item theories about willpower scale (Job et al., 2010; Job, Walton, Bernecker, & Dweck, 2015). This scale consists of three items measuring people's endorsement of a limited account of willpower (e.g., "*After a strenuous mental activity my energy is depleted and I must rest to get it refueled again*") and three items measuring people's endorsement of a nonlimited account of willpower (e.g., "*My mental stamina fuels itself; even after strenuous mental exertion I can continue doing more of it*"). Importantly, because the original scale mainly refers to mental energy, we removed every instance of the word "mental." We did this so that the scale reflects a more domain-general measure of energy availability. Responses were provided on a 6-point scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). Items referring to the limited-energy account were reverse-scored so that higher values represent greater agreement with the nonlimited-energy account. Responses to all items were averaged, such that higher scores on this composite indicate stronger endorsement of the nonlimited energy account (α = .90).

Domain-specific energy. To assess the degree to which people differentiate between the energy for physical, mental, social, and emotional activities, we included four items: "*Compared to the peak of your life, how much energy do you have currently available for physical [mental] [social] [emotional] activities?*" on a 6-point scale ranging from 0 (*much less*) to 5 (*the same*).

In addition, we included a more idiographic measure of energy availability by asking participants first to list two demanding activities for each domain that are typical for them, and then to answer the same items with respect to these activities. For example, if a person indicated that exercising and biking were physically demanding for her, the corresponding two items for the physical domain would read "*Compared to the peak of your life, how much energy do you have currently available for exercising [biking]*?" We averaged the two domain-specific items to create a composite score for each of the four domains (αs between .66 and .75).

Within- and cross-domain energy spillover. Do people perceive to have a single or multiple pool(s) of energy available for activities affecting different domains? For instance, does exercising at the gym influence the amount of energy available for writing a manuscript or meeting with friends? To explore such spillover effects, we included the following items: "*After demanding physical [mental] [social] [emotional] activities, how much energy do you have available for physical [mental] [social] [emotional] activities?*" on a 7-point scale ranging from -3 (*much less*), 0 (*the same*), to +3 (*much more*). This resulted in a total of 4 (strained domain) x 4 (spillover domain) = 16 items. In addition to exploring perceived cross-domain spillover, this also enabled us to examine within-domain spillover (e.g., "*After demanding physical activities, how much energy is available to you for further physical activities?*").

Dispositional exhaustion and recovery. The General Exhaustion and Recovery Scale (Cardini et al., 2019) measures dispositional exhaustion and recovery as two separate dimensions. The exhaustion dimension consists of 8 items (e.g., "*In general, I feel weak*"; α = .87). The recovery dimension consists of 5 items (e.g., "*In general, I feel energized*"; α = .80). Items were measured on a 6-point scale ranging from 0 (*not at all*) to 5 (*very much*). We computed mean scores for the exhaustion and recovery subscales.

Table 3

Means, Standard Deviations, and Zero-Order Correlations for Dispositional Measures.

Measure	*M* (*SD*)	1	2	3	4	5	6	7	8
1. Recovery[a]	3.24 (0.94)	–							
2. Exhaustion[a]	1.21 (0.94)	**-.60**	–						
3. Positive Mood[a]	3.82 (0.91)	**.64**	**-.77**	–					
4. Wakefulness[a]	3.11 (1.07)	**.61**	**-.72**	**.75**	–				
5. Calmness[a]	3.34 (1.00)	**.41**	**-.56**	**.67**	**.59**	–			
6. Life satisfaction[b]	4.50 (1.10)	**.47**	**-.60**	**.69**	**.53**	**.46**	–		
7. Physical health[b]	4.36 (1.13)	**.39**	**-.42**	**.46**	**.42**	**.33**	**.46**	–	
8. Energy belief[ac]	2.47 (1.11)	**.47**	**-.30**	**.30**	**.39**	**.19**	**.19**	**.24**	–
9. Age in years	50.40 (20.20)	**.18**	**-.39**	**.38**	**.43**	**.43**	**.31**	.07	**.19**

Note. $N = 276$. The critical correlation coefficient for $\alpha = .05$ (two-tailed) is .12. Bold correlation coefficients remain significant ($p < .05$) after correcting for multiple testing (Holm-Bonferroni).

[a]Measured on a 6-point scale from 0 (lower expression) to 5 (higher expression).

[b]Measured on a 7-point scale from 0 (lower expression) to 6 (higher expression).

[c]Higher scores indicate higher agreement with the non-limited energy belief.

Dispositional mood state. The Multidimensional Mood State Questionnaire (German short version; Steyer et al., 1997) measures three bipolar dimensions of psychological functioning: Wakefulness (vs. tiredness; 4 items, $\alpha = .85$), good mood (vs. bad mood; 4 items, $\alpha = .86$), and calmness (vs. nervousness; 4 items, $\alpha = .79$) on a 6-point scale ranging from 0 (*not at all*) to 5 (*very much*). Sample items include "*In general, I feel rested*" for wakefulness, "*In general I feel content*" for positive mood, and "*In general, I feel composed*" for calmness. We computed mean scores for the wakefulness, positive mood, and calmness subscales.

Procedure. The study consisted of an online questionnaire that was programmed and administered on the SoSci Survey platform (www.soscisurvey.de). Upon giving informed consent, participants first filled out a sociodemographic questionnaire followed by the adapted theories about willpower scale (Job et al., 2010; Job et al., 2015). Next, they were familiarized with the concept of spending energy in the physical, mental, social, and emotional domain. More specifically, we gave examples of how energy might be spent for activities typically associated with these domains (e.g., climbing the stairs as physical, doing crossword puzzles as mental, spending time with friends as social, and experiencing certain emotions as emotional activities). They then rated the degree of energy they had currently available to spend on the different domains compared with their perceived "energy peak." We made sure to specify that one's energy peak for a certain domain might be located in the past, present, or future. Next, for each domain they listed two demanding activities that they typically encounter in their daily lives, and again rated their current energy availability for these activities compared with their peak energy availability. In a next step, we introduced them to the possibility of energy spillover, namely that people might perceive to have different "energy pools" available for the different domains or conversely, that people might perceive to draw energy from a single pool no matter which domain is affected. Participants then rated the extent to which they experienced such within- and cross-domain spillover in their daily lives. Lastly, they filled out dispositional measures of recovery and exhaustion (Cardini et al., 2019), as well as mood, wakefulness, and calmness (Steyer et al., 1997). After the debriefing, participants were offered the opportunity to enter a raffle of ten Amazon vouchers à 30 Swiss francs.

Statistical analysis. We used Pearson product-moment correlations to examine the degree of interdependence among the variables of interest. Spearman's rank correlations yielded the same pattern of results. Thus, we only report the Pearson correlation coefficients. We conducted all analyses in R (R Core Team, 2018) using the psych package (Revelle, 2018) for descriptive statistics and the stats package (R Core Team, 2018) for the correlations.

Results

Preliminary analyses. The variables of interest had no missing data, with one exception: Because people might differ in the extent to which they perceive activities of a certain domain as effortful, we gave them the option not to list any domain-specific demanding activities. For the physical domain, n = 6 people listed no such activities and n = 20 people listed only one activity (mental: n = 8 and n = 22; social: n = 10 and n = 37; emotional: n = 27 and n = 68). Four persons did not list any demanding activities. Thus, for the statistical analyses dealing with the idiographic measures of domain-specific energy availability, we excluded those persons who did not report any demanding activities in the respective domain.

Lay beliefs about energy, age, and subjective well-being. As can be seen in Table 3, we found a small positive correlation between endorsing the nonlimited energy account and age. Table 3 further reveals small and medium positive correlations of both age and endorsing the nonlimited energy account with various indicators of subjective well-being: Older people as well as people who endorse a nonlimited energy account generally reported to be more recovered, less exhausted, in a better mood, more awake, calmer, and more satisfied with their lives.

Table 4

Means, Standard Deviations, and Zero-Order Correlations for Domain-Specific Energy.

	General				Idiographic[a]			
Available energy for...	1	2	3	4	1	2	3	4
1. Physical activities[b]	–				–			
2. Mental activities[b]	**.20**	–			**.41**	–		
3. Social activities[b]	**.20**	**.36**	–		**.44**	**.43**	–	
4. Emotional activities[b]	.15	**.34**	**.43**	–	**.43**	**.40**	**.50**	–
5. Age in years	**-.22**	.07	.13	.12	.05	**.20**	**.18**	.14
M	3.07	3.93	3.44	3.78	3.56	3.92	3.64	3.83
SD	1.36	0.92	1.25	1.18	1.24	1.00	1.18	1.19

Note. $N = 276$. The critical correlation coefficient for $\alpha = .05$ (two-tailed) is .12. Bold correlation coefficients remain significant ($p < .05$) after correcting for multiple testing (Holm-Bonferroni).

[a]Effective sample size varies due to pairwise deletion.

[b]Measured on a 6-point scale from 0 (*much less*) to 5 (*the same*).

Domain-specific energy availability and age.

Activities in general. As can be seen in Table 4, as expected, we found a small negative correlation between available energy for physical activities and age. Contrary to our expectation, the perceived availability of energy for mental activities did not change with age.

Table 5

Means, Standard Deviations, and Zero-Order Correlations for Within- and Cross-Domain Energy Spillover.

	After Physical Exertion				After Mental Exertion			
Available energy for...	1	2	3	4	1	2	3	4
1. Physical activities[a]	–				–			
2. Mental activities[a]	**.36**	–			**.23**	–		
3. Social activities[a]	**.37**	**.62**	–		**.33**	**.36**	–	
4. Emotional activities[a]	**.31**	**.59**	**.74**	–	**.25**	**.33**	**.54**	–
5. Age in years	.02	-.10	**-.19**	**-.16**	-.11	**.27**	**-.18**	.10
M	-1.09	0.26	0.26	0.32	0.35	-0.47	0.06	-0.08
SD	1.43	1.33	1.30	1.30	1.34	1.32	1.24	1.13
	After Social Exertion				**After Emotional Exertion**			
Available energy for...	1	2	3	4	1	2	3	4
1. Physical activities[a]	–				–			
2. Mental activities[a]	**.40**	–			**.45**	–		
3. Social activities[a]	**.33**	**.53**	–		**.37**	**.59**	–	
4. Emotional activities[a]	**.20**	**.40**	**.58**	–	**.26**	**.57**	**.67**	–
5. Age in years	**-.18**	.02	.00	.02	-.03	**.23**	.08	**.15**
M	0.10	0.04	-0.49	-0.20	0.09	-0.40	-0.41	-0.60
SD	1.25	1.10	1.34	1.28	1.44	1.29	1.38	1.44

Note. $N = 276$. The critical correlation coefficient for $\alpha = .05$ (two-tailed) is .12. Bold correlation coefficients remain significant ($p < .05$) after correcting for multiple testing (Holm-Bonferroni).

[a]Measured on a 7-point scale from -3 (*much less*), 0 (*the same*), to +3 (*much more*).

Idiographically chosen activities. Table 4 further shows that when asked about the energy available for individually selected physical activities, older adults no longer reported to have less energy available. In contrast, older adults reported to have more energy available for individually listed mental and social activities.

Within- and cross-domain energy spillover and age.

Within-domain. As can be seen in Table 5, people generally reported to have less energy available for activities after having been engaged in activities of that same domain beforehand. For instance, the mean energy available for physical activities after prior physical exertion was -1.09 on a scale from -3 (*much less*) to +3 (*much more*). This mean value significantly differed from the scale midpoint (which corresponds to 0 [*the same*]), $t(275) = -12.71$, $p < .001$, 95% CI of the mean difference [-1.26, -0.92], $d = -0.77$. In comparison, although significant (all ps < .001), the mean deviations from the scale midpoint in the other domains had small effect sizes (ds between -0.36 and -0.42).

We found small positive correlations between mental and emotional within-domain spillover with age. In other words, after prior mental and emotional exertion, older adults reported to have *more* energy available for further mental and emotional activities.

Cross-domain. Table 5 further shows that people reported little to no cross-domain energy spillover (ds between -0.31 and 0.26). However, we found domain-specific age effects: After physical exertion, older adults reported to have less energy available for social and emotional activities. Similarly, after mental exertion, older adults reported to have less energy available for social activities. After social exertion, older adults reported to have less energy available for physical activities. Finally, after emotional exertion, older adults reported to have more energy available for mental activities.

Brief Discussion

Energy can be viewed as a general-purpose resource as almost all goal pursuit requires the investment of energy. Study 1 investigated if energy is one of the resources that people perceive to decline with age. Do older adults feel generally more exhausted because their subjective energy level is lower than that of younger age groups? Moreover, we explored if, similar to willpower, people differ regarding their subjective beliefs about energy as a domain-general resource, such that spending it for a goal in one life domain also depletes it for pursuit of a goal in a different life domain versus energy as domain-specific.

The results of Study 1 suggest that, as people grow older, they are more likely to believe that energy – similar to willpower (Job et al., 2018) – is a nonlimited resource for goal pursuit, and also perceive to have more energy available for personally relevant mental activities. Furthermore, consistent with the important role of social relations in old age (Antonucci et al., 2010; Carstensen et al., 1999), older adults perceive to have more energy available than younger age groups for social activities in their daily lives. However, older adults also perceive to have less energy available for physical activities in general, but not for the physical activities that they select for themselves. One reason for this pattern of findings might be that older adults – faced with declines in physical and cognitive functioning (Baltes et al., 2006; Baltes & Smith, 2003) – become increasingly selective in the engagement of effort (Hess, 2014; Hess et al., 2016) into goals (Freund, 2008). If older adults perceive to have less energy available for physical activities in general, they might select their most important physical and mental activities on which they focus their remaining energy. As a consequence, these activities then correspond to the available energy levels well into old age.

Older adulthood is associated with more pronounced cross-domain energy spillover, predominantly in the physical domain: After physical exertion, older adults perceive to have less energy available for social, emotional and, to a lesser degree, mental activities. This finding is in line with our proposition (Cardini & Freund, 2019a) that older adults, who are increasingly motivated to maintain their current level of functioning and prevent further losses (Freund & Baltes, 1998; Freund et al., 2012), are more sensitive toward opportunity costs. We argue that an increase in opportunity costs experienced during an ongoing activity is an indication that the activity's cost-benefit ratio has turned unfavorable, and that one's energy is better spent on a more valuable activity. Thus, the hypothesized heightened sensitivity toward opportunity costs might be adaptive for older adults because it allows them to disengage earlier from demanding activities that incur high energy costs and, as a result, to protect their remaining goal-relevant resources for more fruitful goal pursuits. As a next step, we conducted a study testing more directly the hypothesized age-differential effects of opportunity costs during and after a demanding physical activity.

Study 2

Based on the findings in Study 1 demonstrating that older adults generally do not report to overextend their energy levels, in Study 2 we tested the hypothesis that older adults are more sensitive toward opportunity costs than younger age groups (Cardini & Freund, 2019a). If, as we interpret the pattern of results in Study 1, older adults do in fact shield their subjective energy by selecting activities that match their perceived available energy, they should be particularly sensitive regarding the amount of energy they spend on a given activity compared to alternative activities. In other words, in order to preserve their subjective energy, older adults are expected to be more sensitive to opportunity costs than younger age groups. A strong test of this hypothesis is that older adults are generally more sensitive to opportunity costs than younger age groups, even when activities do not require any particular investment of energy.

Based on these considerations, we designed Study 2 as follows: Participants first completed a demanding physical activity (i.e., a 20-minute high-intensity interval training), which served as a physical exhaustion induction. They were then given the opportunity to recover from this induced exhaustion (i.e., listen to a 20-minute relaxing mindfulness instruction video; The Honest Guys – Meditations – Relaxation, 2016). During the exhaustion and recovery period, we repeatedly assessed subjective exhaustion and recovery, opportunity costs, and other variables associated with exhaustion and recovery. We expected that older adults, compared to younger adults, report a steeper increase in opportunity costs and exhaustion during the exhaustion period, as a motivational cue for disengagement (Cardini & Freund, 2019a).

To avoid age-based stereotype threat (Hess, Growney, & Lothary, 2019; Lamont, Swift, & Abrams, 2015), we made sure to keep the data collections of the younger and middle-aged adults separate from those of the older adults. Furthermore, younger and older adults might perceive the chosen physical exercise as differently demanding. Therefore, to maximize the equivalence in perceived effort across age groups and to address issues of external validity (Freund & Isaacowitz, 2013), we instructed participants to exert the maximum amount of effort that they would also be willing to spend for a similar activity in their everyday lives. Furthermore, we settled on a duration of 20 minutes for the physical exercise, because older adults prefer to engage in physical activity continuously for up to 30 minutes (e.g., Amireault, Baier, & Spencer, 2019).

Method

Participants. We determined the sample size based on an a priori power analysis with G*Power (Version 3.1; Faul et al., 2009), which revealed a minimum sample size of 50 participants per age group ($N = 150$) to detect a small effect of interest ($f = .10$) with $\alpha = .05$ and 95% power for a repeated measures ANOVA with within-between person interactions. Our inclusion criteria for this study were as follows: Participants had to be between 18 and 100 years old, must not have taken part in prior similar studies (see Cardini & Freund, 2019b), and had to be physically healthy, as determined by various questions related to cardiovascular health (e.g., not suffer from high blood pressure, breathing difficulties, pain after physical exertion, blood pressure irregularities).

Initially, 232 participants were recruited from two participant pools of the Department of Psychology and the Life-Management lab at the University of Zurich, local gyms, and senior citizen's sport clubs, and filled out the online screening questionnaire. Of those, 153 persons took part in the main study. Two participants had to be excluded: One person reacted negatively toward the male voice in the mindfulness video and withdrew participation; one person did not fill out the paper-pencil items correctly. Furthermore, the paper-pencil data from four persons could not be matched with their data from the online screening questionnaire. This resulted in a final N of 147 participants who completed the study and who were included in the statistical analyses. Of those, n = 49 were younger (18-34 years; 76% women), n = 48 middle-aged (35-59 years; 56% women), and n = 50 older adults (60-86 years; 42% women). As reimbursement, participants received 15 Swiss francs or course credit. Upon request, they received an instruction manual on how to continue the exercises at home and were given the YouTube link to the mindfulness-based video.

Measures. The means, standard deviations, and zero-order correlations of the study variables are depicted in Table 6. Again, all items reported in this study were either translated or created in German.

Dispositional exhaustion, recovery, and mood. We again included the General Exhaustion and Recovery Scale (Cardini et al., 2019) and the Multidimensional Mood State Questionnaire (Steyer et al., 1997) as dispositional measures. Reliabilities (αs) ranged between .68 and .89.

Table 6

Means, Standard Deviations, and Zero-Order Correlations for Dispositional Measures.

Measure	*M* (*SD*)	1	2	3	4	5	6	7	8
1. Recovery[a]	3.08 (0.76)	–							
2. Exhaustion[a]	0.84 (0.82)	**-.44**	–						
3. Positive Mood[a]	4.03 (0.79)	**.52**	**-.74**	–					
4. Wakefulness[a]	3.46 (0.91)	**.58**	**-.72**	**.74**	–				
5. Calmness[a]	3.51 (0.82)	**.33**	**-.60**	**.68**	**.65**	–			
6. Life satisfaction[a]	3.86 (0.79)	**.31**	**-.49**	**.71**	**.44**	**.44**	–		
7. Physical health[a]	3.82 (0.88)	**.44**	**-.38**	**.49**	**.34**	**.33**	**.49**	–	
8. Fitness[a]	3.32 (0.90)	**.43**	**-.31**	**.37**	**.36**	**.23**	**.32**	**.68**	–
9. Age in years	48.41 (20.26)	.06	**-.32**	**.24**	**.37**	**.23**	.10	-.07	-.04

Note. $N = 147$. The critical correlation coefficient for $\alpha = .05$ (two-tailed) is .16. Bold correlation coefficients remain significant ($p < .05$) after correcting for multiple testing (Holm-Bonferroni).

[a]Measured on a 6-point scale from 0 (lower expression) to 5 (higher expression).

Situational exhaustion, recovery, and opportunity costs. Due to practical constraints, we administered the state items during the exhaustion and recovery period using paper-pencil questionnaires. For the sake of brevity, we operationalized each item as a bipolar visual analogue scale ranging from -5 to +5, with a neutral zero point in the middle (Russell & Carroll, 1999). We used visual analogue scales because they have some advantages over Likert-type scales (e.g., Chang & Little, 2018; Sung & Wu, 2018). We decided for a bipolar and against a bivariate approach because, as Russell (2017, p. 116) put it, “in most circumstances a person feels either good or bad but not both,” adding that mixed emotions occur only in rare events, such as "when a stimulus event is highly salient (a powerful film, college graduation and so on)."

We assessed subjective exhaustion and recovery with two items targeting the physical and mental domain with, "*How do you feel right now physically [mentally]*?" on a scale ranging from -5 (*very exhausted*) and +5 (*very recovered*), and perceived opportunity costs with, "*Right now, would you rather…*" with -5 (*continue this activity?*) and +5 (*do something else?*) as verbal anchors. Within-person reliabilities were good (R_{Cn}s between .84 and .86; Cranford et al., 2006), indicating that systematic change over time was reliably measured by these variables.

Time-varying covariates. Although not the focus of this study, we included mood and time perception as time-varying covariates because we have proposed them as further indicators of exhaustion and recovery (Cardini & Freund, 2019a): "*What is your momentary mood?*" with -5 (*very bad*) to +5 (*very good*) and, "*How does time pass for you right now?*" with -5 (*very slowly*) to +5 (*very fast*) as verbal anchors. Furthermore, we included a measure of boredom/interest: "*How do you perceive this activity right now*?" with -5 (*very boring*) and +5 (*very interesting*) as verbal anchors. The results concerning these variables are reported in Tables A6 and A7 in Appendix A.

Time as independent variable. We coded the time variable for the exhaustion period from 0 to 10, such that 0 represents the baseline measurement occasion (i.e., immediately before the exercise) and 10 represents the last measurement occasion of the exhaustion period (i.e., 20 minutes into the exercise). Because of the seamless transition between the exhaustion and recovery period, the first measurement occasion of the recovery period coincided with the last measurement occasion of the exhaustion period (i.e., 20 minutes into the exercise).

The last measurement occasion of the recovery period was located 18 minutes into the mindfulness video. Therefore, we coded the time variable for the recovery period from 0 to 9.

The time points were equally spaced (i.e., two minutes). This scaling of time implies that a linear slope for time estimates the change in the dependent variable from one measurement occasion to the next (i.e., every two minutes).

Procedure. Participants first read a detailed description of the study, the inclusion criteria, and gave their informed consent for participation. They were then screened for their cardiovascular health. Next, they filled out a sociodemographic questionnaire. Finally, they reported on their perceived physical fitness, weekly exercise frequency, dispositional exhaustion and recovery (Cardini et al., 2019), as well as mood, wakefulness, and calmness (Steyer et al., 1997). All of these variables were assessed online.

The main part of the study was conducted in a laboratory room in groups with up to eight participants. After having been familiarized with the visual analogue scale items through a brief demonstration, participants filled out the paper-pencil questionnaire for the first time, serving as the baseline measure. Next, they participated in the 20-minute high intensity interval training (adopted from Kaftan & Freund, 2019), which consisted of five 4-minute training units. One training unit consisted of a bout of physical exercises (e.g., jumping jacks, push-ups, plank, sit-ups). Each exercise was maintained for 20 seconds and followed up with 10 seconds of rest. The exercises were displayed on a video in front of the participants. The video was accompanied by motivational music. The experimenter (either the first author, a trained student assistant, or a trained intern) participated in the physical exercise, to further motivate participants to spend effort. Every two minutes, the experimenter paused the video and prompted participants to quickly fill out the next paper-pencil questionnaire before resuming the exercises.

Immediately upon finishing the training, participants filled out the last paper-pencil questionnaire pertaining to the exhaustion period. This measurement occasion simultaneously served as the baseline for the recovery period. Participants were then instructed to lie down on yoga mats and make themselves as comfortable as possible. They were told that they would now have the opportunity to recuperate from the physical exercise through listening to a relaxing video. As soon as all participants were lying down, the experimenter started the mindfulness-based relaxation video (The Honest Guys – Meditations – Relaxation, 2016). This video consisted of a very calm male voice giving mindfulness instructions. The video was accompanied by tranquil music, and the sounds of splashing waves and seagulls. Every two minutes, participants were gently prompted by the experimenter to fill out the next batch of paper-pencil items. The timing of the instructions was carefully chosen, so as to coincide with muted parts of the video. The video ended after 20 minutes, and participants were debriefed and given their preferred reimbursement (15 Swiss francs or course credit).

Statistical analysis. To address the research question of this study, we focused on age-related differences in physical and mental exhaustion and opportunity costs during the exhaustion period (see Appendix A for the analyses concerned with age-related differences in mood, subjective time perception, and interest during the exhaustion period [Table A6] and for all time-varying variables during the recovery period [Table A7], as well as analyses of the correlated change between these variables [Tables A8 and A9]). We analyzed age-related differences in the time course of the variables of interest using univariate conditional multilevel growth curve models with measurement time (11 time points during the exhaustion period), the mean-centered continuous age variable, and the interaction between time and age serving as independent variables. Because these data were longitudinal, we allowed for a simple autocorrelative error structure (AR[1]) and, where applicable, accounted for heteroscedasticity of the variables over time.

We conducted all analyses in R (R Core Team, 2018). We used the psych package (Revelle, 2018) for descriptive statistics, the nlme package (Pinheiro et al., 2018) for the multilevel model parameter estimations, and the r2glmm package (Jaeger, 2017) for calculating a suitable R^2 for our models. We followed the suggestions of Bolger and Laurenceau (2013) for reporting multilevel analyses.

Results

Preliminary analyses. The initial multilevel analysis dataset consisted of 147 (participants) x 11 (measurement occasions) = 1,617 observations. Due to inattention, one person did not fill out the paper-pencil items at one measurement occasion. Thus, the final analysis dataset consisted of 1,616 observations.

Model building. All time-varying variables showed substantial between-person variance (ICCs between .50 and .64), confirming the nested structure of the data (measurement occasions nested in persons) and necessitating the use of multilevel modeling (Bliese, 2000). We began the model building process by comparing random-intercept-only models to random-intercept-and-slope models. In a next step, we added an autocorrelative error structure (AR[1]) to the models. Then, we tested for heteroscedasticity. Given that these models are nested, we decided on the best-fitting model using the chi-square likelihood ratio test under restricted maximum likelihood estimation. The best-fitting models across all time-varying variables were random-intercept-and-slope models that account for autocorrelation, but not for heteroscedasticity. In other words, participants varied substantially on all time-varying variables with regard to their initial intercepts (i.e., baseline measurement before the exercise), as well as in their rate of change over the exhaustion period.

To examine the shape of the growth curves, we tested which polynomial degree (i.e., linear, quadratic, cubic) best represented the regression line of the time-varying variables. For each variable, we compared the model with a linear fixed effect of time with a model encompassing both a linear and quadratic fixed effect of time, and so on. Given that these comparisons involve non-nested models (i.e., different fixed effects structures), we decided on the best-fitting model using the AIC and BIC under maximum likelihood estimation, with lower values indicating better model fit.

Modeling the time courses. The results for the time courses are shown in Table 7 (fixed effects of time) and the left panels of Figure 5. Table 7 depicts two sets of parameter estimates. The first set, the fixed effects, are the results for the average person in the sample. The fixed effects of time are represented by the thick black lines in the left panels of Figure 5. The second set in Table 7 lists the random effects. These random effects describe variation at two levels of analysis: At the between-person level, they model the extent to which persons deviate from the typical person in the sample. At the within-person level, they model the extent to which the raw data varies from the model-predicted values. The between-person random effects are visualized in the left panels of Figure 5 by the variability in individual regression lines (thin grey lines) around the average regression line.

Main effects of time, age, and their interaction.

Physical recovery. As can be seen in Table 7, there was a significant main effect of all polynomials of time on physical recovery: The typical participant in the sample reported an initial decrease in physical recovery, followed by a period of less steep decrease, and at the end again reported a steeper decrease in physical recovery (see Figure 5A). In contrast, there was no significant main effect of age on physical recovery. All Age x Time interactions were significant. However, the effect sizes of the interactions of age with the quadratic and cubic polynomials of time were near zero. Therefore, we only interpret the interaction of age with the linear polynomial of time, which represents age-related differences in the initial rate of change.

To better understand these cross-level interactions and to test for significant differences between younger and older adults, we replaced the continuous age predictor with the discontinuous age group predictor (coded 0 = younger adults, 1 = middle-aged adults, 2 = older adults) and reran the analysis. The results are visualized in Figure 5B. Compared to younger and middle-aged adults, older adults showed a steeper initial decrease in physical recovery, followed by a more pronounced flattening of the curve, and at the end of the exercise again reported a steeper decline in physical recovery (all *p*s < .001). In contrast, the younger and middle-aged adults did not significantly differ in their time courses (*p*s between .16 and .44).

Mental recovery. There were also statistically significant, although less pronounced, main effects of all polynomials of time on mental recovery: The typical participant in the sample reported a slight initial increase in mental recovery, followed by a slight decrease (see Figure 5C). There was a significant main effect of age on mental recovery. The Age x Time interactions were significant.

As can be seen in Figure 5D, compared to younger adults, older adults showed a less pronounced initial increase in mental recovery ($p = .007$) and a less pronounced later decline ($p = .001$). The same pattern of results held when comparing younger to middle-aged adults ($p = .014$ and $p = .005$, respectively). In contrast, middle-aged and older adults did not significantly differ in their time courses ($p = .817$ and $p = .744$, respectively).

Table 7

Multilevel Growth Curve Models for Physical Recovery, Mental Recovery, and Opportunity Costs During the Exhaustion Period as a Function of Time, Age, and Their Interaction.

	Dependent Variable		
Fixed Effects	Physical Recovery	Mental Recovery	Opportunity Costs
Intercept	**1.79 [1.52, 2.06]**	**1.98 [1.69, 2.27]**	**-2.04 [-2.42, -1.65]**
Time	**-0.99 [-1.15, -0.84]**	**0.17 [0.09, 0.26]**	**-0.45 [-0.65, -0.25]**
$Time^2$	**0.12 [0.09, 0.15]**	**-0.02 [-0.03, -0.02]**	**0.13 [0.09, 0.17]**
$Time^3$	**-0.01 [-0.01, -0.00]**	–	**-0.01 [-0.01, -0.00]**
Age	0.01 [-0.00, 0.02]	**0.02 [0.01, 0.04]**	-0.01 [-0.03, 0.01]
Age x Time	**-0.02 [-0.03, -0.01]**	**-0.01 [-0.01, -0.03]**	**0.03 [0.02, 0.04]**
Age x $Time^2$	**0.00 [0.00, 0.00]**	**0.00 [0.00, 0.00]**	**-0.01 [-0.01, -0.00]**
Age x $Time^3$	**-0.00 [-0.00, -0.00]**	–	**0.00 [0.00, 0.00]**
Random effects			
Between-person			
Intercept	1.40	1.70	1.98
Time	0.60	0.41	0.63
$Time^2$	0.05	0.03	0.05
$Time^3$	0.00	–	–[a]
Within-person			
Residual	0.92	0.87	1.33
AR(1)	.26	.21	.52
Marginal R^2	.13	.01	.07
Conditional R^2	.85	.79	.79

Note. $N = 147$, 11 measurement occasions, 1,616 observations. Time is coded 0 to 10. Age is mean-centered. The fixed effects are reported as unstandardized regression coefficients (their 95% CIs in brackets). The fixed effects in bold are significant (their 95% CIs do not include 0). The random effects are reported as standard deviations and correlations. Marginal R^2 depicts the proportion of variance explained by the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined (Nakagawa & Schielzeth, 2013; Johnson, 2014).

[a]Due to model convergence issues, we had to omit this random effect parameter.

Opportunity costs. The main effects of all polynomials of time on perceived opportunity costs were significant: The typical participant in the sample reported an initial decrease in opportunity costs, followed by a period of increase in opportunity costs, and at the end reported a less pronounced increase in opportunity costs (see Figure 5E). There was no significant main effect of age on opportunity costs. All Age x Time interactions were significant.

Figure 5F indicates that compared to younger and middle-aged adults, older adults reported a steeper initial increase in opportunity costs, a less pronounced increase afterwards, and again a more pronounced increase in the end (all ps < .001). In comparison, middle-aged adults did not significantly differ from younger adults in their time course (ps between .736 and .957).

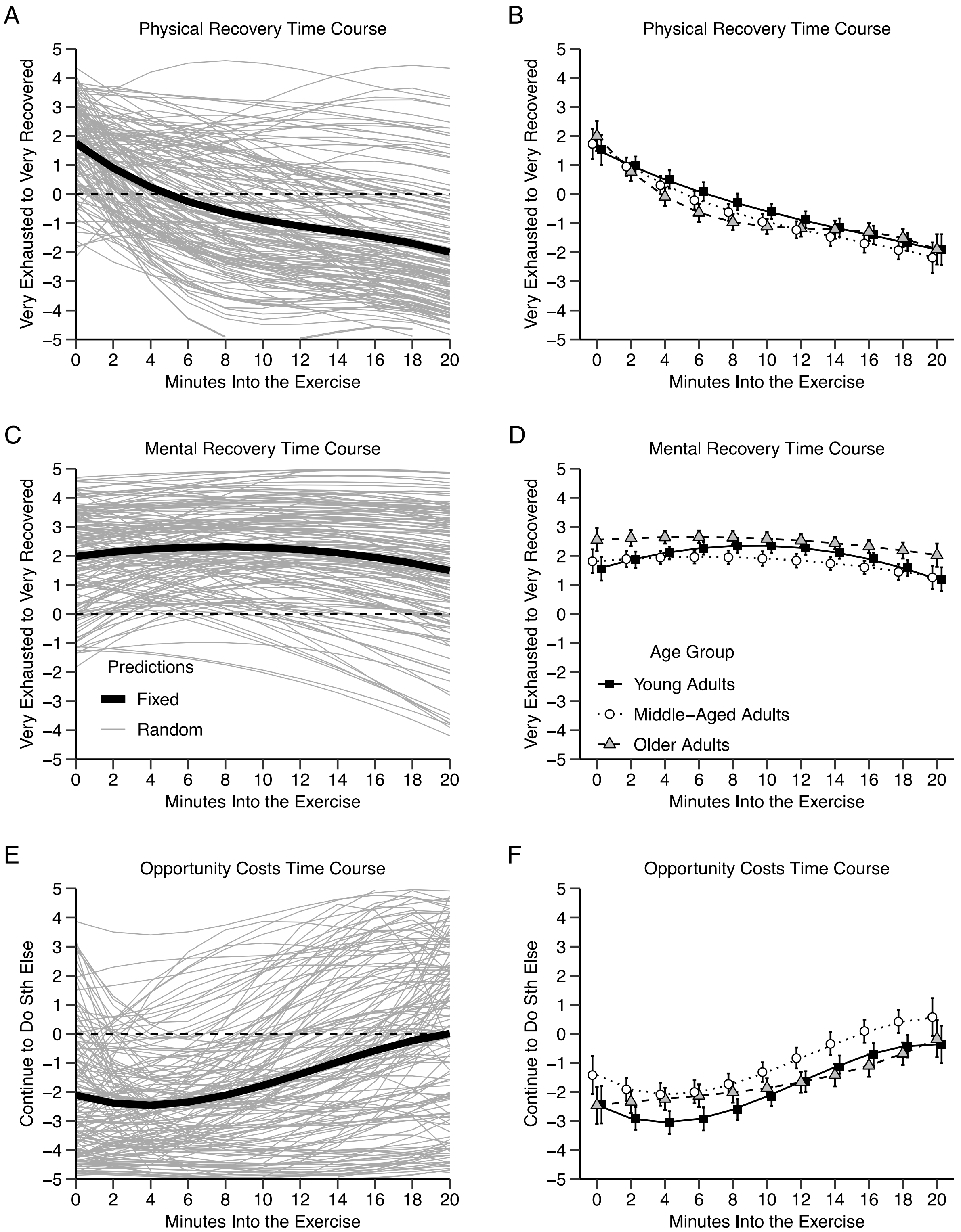

Figure 5. Spaghetti plots of the fixed and random effects of time (panels A, C, E) and Age x Time interaction plots (panels B, D, F). Error bars represent 95% confidence intervals.

Brief Discussion

Study 2 partly supported our hypothesis that older adults are more sensitive toward opportunity costs (Cardini & Freund, 2019a). Compared to younger adults, older adults reported a steeper initial increase in exhaustion and opportunity costs during demanding physical exercise. Contrary to our expectations, however, younger and older adults again ended up at similar levels of exhaustion and opportunity costs shortly before the completion of the exercise (see Figure 1D and 1F). Thus, it seems that the hypothesized age-related differences in the rate of change in exhaustion and opportunity costs are especially prevalent at the beginning stages, but less so at the advanced stages of short-term goal pursuit.

Study 2 further showed that older adults reported nearly stable levels of mental recovery during the physical exercise, whereas younger adults reported more pronounced changes in mental recovery over time. This result is in line with the finding of Study 1 that older adults are more likely to endorse a nonlimited account of mental energy, due to their enhanced autonomy related to the engagement in demanding tasks (Job et al., 2018).

General Discussion

A central tenet of lifespan psychology holds that development entails the joint occurrence of gains and losses in all phases of life (Baltes, 1987; Labouvie-Vief, 1981). Older adulthood is characterized by normative declines in physical and cognitive functioning (Baltes et al., 2006; Baltes & Smith, 2003), yet at the same time is accompanied by a marked increase in autonomy and positive emotional experience (e.g., Carstensen et al., 2011; Ryff, 1995). Here, we examined if this age-related changing ratio of gains and losses is reflected in older adults' lower subjective availability of energy for goal pursuits across different functional domains (i.e., physical, mental, social, emotional activities). We found that older adults perceive to have less energy available for physical activities in general. However, older adults did not report having less energy available for physical activities that are personally relevant to them, and reported having even more energy available for personally relevant mental and social activities. We further found that older adults, compared to younger adults, report a steeper initial increase in subjective exhaustion and opportunity costs during a demanding physical activity, but show comparable levels again of both at the close.

Age-Related Differences in Subjective Energy Availability Vary Across Domains

Compared to younger adults, older adults perceive to have more energy available for individually selected social activities. This might be due to the change in goal priorities across adulthood: According to socio-emotional selectivity theory younger adults are more likely to pursue future-oriented growth goals aimed at optimizing knowledge, whereas older adults tend to prioritize present-oriented goals aimed at maximizing emotional meaning (Carstensen, 2006; Carstensen et al., 1999).

In line with selective engagement theory (Hess, 2014) and lifespan models of developmental regulation (e.g., Freund, 2008; Freund & Baltes, 2000), the increasing adaptiveness of carefully selecting one’s goals based on one’s remaining energy in older adulthood might explain the discrepancy between older adults' available energy for physical and mental activities in general compared to those that are personally relevant to them. Because of their increasing resource constraints, older adults might choose (1) not to engage in or (2) not to spend a lot effort on very demanding physical and mental activities. Instead, they might opt to engage only in physical and mental activities that they deem manageable at their current level of functioning and that are personally relevant to them. The present findings align with propositions that older adults remain highly functioning in settings that are important to them (Artistico, Cervone, & Montes Garcia, 2019; Baltes, 1997; Cornelius & Caspi, 1987; Blanchard-Fields, 2007), perhaps due to enhanced pragmatic wisdom in handling everyday life challenges (Baltes & Staudinger, 2000).

While people generally do not report high levels of cross-domain energy spillover, the finding that older adults tend to report more cross-domain energy spillover could be explained by the fact that older adults tend to differentiate less between functional domains, perhaps “because they might have experienced the actual connectedness of functioning in different life domains (e.g., physical health facilitates getting together with friends and might, thereby, contribute to social relationships)” (Mustafić & Freund, 2012b, p. 69).

One alternative explanation for these results is that older adults might be affected by self-worth enhancing biases that contribute to more optimistic beliefs about their current level of functioning across various domains, especially when comparing themselves to their same-aged peers (Hess, 2006; Riediger, Voelkle, Schaefer, & Lindenberger, 2014). We tried to address this concern by having participants rate their currently available energy for a domain compared to their *own* energy peak for that domain, and we anticipated that this instruction would lessen the impact of such social downward comparison biases on older adults’ ratings.

Age-Related Differences in Exhaustion and Opportunity Costs During Physical Exercise

Despite having similar baseline values, older adults showed a steeper initial increase in subjective exhaustion and opportunity costs during demanding physical exercise than younger adults, but showed comparable levels again at the end of the exercise. This pattern of results partly supports our hypothesis that older adults, compared to younger adults, feel exhausted faster during short-term demanding activity, because they are more sensitive toward increases in opportunity costs (Cardini & Freund, 2019a).

Because we did not assess measures of task performance or task difficulty, we can only speculate about the potential causes of the finding that older and younger adults reported comparable levels of exhaustion and opportunity costs at the end of the exercise. After investing initial physical effort, older adults might have down-regulated their level of engagement by withdrawing further effort to conserve their remaining energy (Brehm, 1975).

According to motivational intensity theory (Brehm & Self, 1989; Richter et al., 2016), the amount of effort one invests into a task is proportional to that task's perceived difficulty, conditional on the expectancy and value of succeeding at said task. In our study, we let participants set their own performance standards for the physical exercise (e.g., number of push-ups they completed during one trial). Thus, the difficulty of the exercises was not fixed but determined individually. In such a malleable scenario, motivational intensity theory predicts that people aim for the highest level of performance that they deem possible and worthwhile. Assuming that older people show a general tendency to conserve their remaining resources, this could have resulted in older adults' withdrawing effort over time.

Alternatively, an unintended consequence of the instruction for the physical exercise (e.g., "please exert as much effort as possible") might have resulted in older adults adopting a goal orientation geared towards optimizing their performance. Freund (2006) demonstrated that older adults show higher persistence (operationalized as invested time and effort) on demanding tasks if the associated goal is to *maintain* their current level of functioning and *prevent* losses of goal-relevant resources (e.g., energy), whereas younger adults show higher persistence on demanding tasks when their goal is to *optimize* their performance. Importantly, these results were shown to be independent of perceived task difficulty. Thus, older adults' withdrawing effort over time might have been a consequence of an induced motivational orientation towards optimization during the physical exercise.

Limitations and Future Directions

The present set of studies has at least two limitations. First, we cannot rule out the possibility of selection bias, especially for the sample of older adults in Study 2. For instance, there was no correlation between perceived physical fitness and age (see Table 6), suggesting that the recruited sample of older adults might have been a selective subsample consisting of particularly healthy individuals. Given the normative declines in physical and cognitive functioning with age (Baltes et al., 2006; Baltes & Smith, 2003), it is thus likely that the participants of Study 2 are not representative of older adults. This limits the generalizability of the findings of Study 2. Furthermore, it might be possible that we did not find more pronounced age-related differences in the increase of exhaustion and opportunity costs in Study 2 because the potential selectivity of the sample of older adults. Supporting this notion, prior research has found that older adults who tend to endorse negative beliefs about aging (e.g., who believe that energy declines with age) are less likely to engage in physical activity (Meisner, Weir, & Baker, 2013). However, note that we *did* find evidence for initial age-related differences in the increase of exhaustion and opportunity costs during a demanding activity, despite a potential selection bias. Thus, although preliminary, we regard this finding as promising and worthy of further investigation.

One possible remedy to avoid a selection bias in a study investigating the investment and perceived levels of energy might be to examine such age-related differences in subjective energy availability in everyday life contexts using the experience sampling method (Larson & Csikszentmihalyi, 2014). First, less physically active older adults might be more inclined to take part in a study about physical or mental effort when they can provide assessments from the comfort of their own homes. Second, capturing the experiences of older adults as they go about their daily routines and move through their personal environments might be more externally valid, as they would mostly provide energy ratings on personally meaningful activities. However, such a “from lab to life” approach comes with its own pitfalls: Contrary to the laboratory setting employed in Study 2 and absent a specific intervention, an experience sampling design allows for less controllability of the type of activities that younger, middle-aged, and older adults engage in, thus making between-person comparisons difficult.

Second, the present studies are correlational in nature. Thus, we cannot determine *why* older adults perceive to have more energy available for personally relevant mental and social activities, or *why* they report initial increases in exhaustion and opportunity costs during demanding physical exercise. Note that this limitation cannot be solved simply by employing an experience sampling design (although some approaches might approximate causal inference; Bolger & Laurenceau, 2013). Thus, another possible avenue for future work is to examine the psychological mechanisms that might underlie these age-related differences by manipulating them in an experiment (Freund & Isaacowitz, 2013). For instance, recent work has shown that perceived opportunity costs can be efficiently manipulated in a laboratory setting (Cardini & Freund, 2019b; Hofmann et al., 2019). If one is interested in understanding whether an increase in opportunity costs leads to the assessment that the current activity is incurring more costs (e.g., draining energy) than benefits (e.g., goal progress), one could manipulate opportunity costs before or during a demanding activity and study the impact of this manipulation on feelings of effort, exhaustion, or activity utility.

Despite these limitations, this set of studies provides the as-yet most comprehensive examination of age-related differences in the subjective availability of energy for goal pursuits targeting different functional domains. Furthermore, it represents the first empirical insight into age-related differences in perceived opportunity costs – a construct of central importance in more recent research on self-regulation, effort, and exhaustion (e.g., Cardini & Freund, 2019a; Hofmann et al., 2019; Kurzban et al., 2013).

PART IV: HOW TO RECHARGE DURING A VACATION: THE ROLE OF DAILY MOOD AND OPPORTUNITY COSTS FOR RECOVERY

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This article has been submitted for publication (2019) in a peer-reviewed journal and is currently under review. Please do not copy or cite without permission of the authors.

Abstract

Leisure experiences impact recovery from everyday life demands. Testing a recent motivational model of recovery, we examined if this also applies to recovery from accumulated strain during a vacation. In the current daily diary study, 147 university students reported their daily recovery, mood, opportunity costs, and subjective time perception over 21 consecutive days (2,342 observations) during the summer break. Multilevel analyses showed that students reported higher recovery on days when they were in a better mood and perceived lower opportunity costs than usual. These results held after controlling for the passage of time and well-established covariates of recovery (i.e., psychological detachment, relaxation, mastery, and control). Supporting the motivational model of recovery, positive mood, the absence of opportunity costs and, to a lesser degree, the perception of time passing quickly contribute to daily recovery during a vacation.

Introduction

Leisure is important for recovery (Kuykendall, Tay, & Ng, 2015; Sonnentag et al., 2017). Be it short breaks during work (Hunter & Wu, 2016), lunch breaks (Bosch, Sonnentag, & Pinck, 2018), evenings (Bennett, Bakker, & Field, 2018), or weekends (Binnewies, Sonnentag, & Mojza, 2010) – the way we spend and experience our free time markedly impacts how successfully we recover from the demands of everyday life. Yet, not all leisure activities promote recovery equally well. For instance, hitting the gym after a stressful day at work may feel reinvigorating for some people, but leave others even more drained. Addressing these individual differences, research suggests that recovery mainly depends on how people *experience* their leisure activities (Newman et al., 2014; Sonnentag & Fritz, 2007). For example, leisure activities facilitate recovery if they enable a person to mentally disengage from work (Sonnentag & Fritz, 2015) or if they satisfy a person's need for autonomy, meaning, and affiliation (Newman et al., 2014).

Different to the research on short-term recovery, surprisingly little is known about how recovery unfolds on larger time scales such as vacations (Sonnentag et al., 2017). An established finding in this area is that people tend to report higher levels of health and well-being at the end compared to the beginning of a vacation, but these benefits fade out soon after work is resumed (De Bloom, Geurts, & Kompier, 2012; De Bloom, Geurts, & Kompier, 2013; De Bloom et al., 2011; De Bloom et al., 2010; De Bloom et al., 2009; Kühnel & Sonnentag, 2011; Syrek, Weigelt, Kühnel, & De Bloom, 2018).

The *processes* underlying the increase in health and well-being over the course of a vacation remain poorly understood, because prior research has largely neglected to investigate the time period during a vacation. To put it in the words of De Bloom et al. (2013, p. 615), "it is essential to open up the black box of vacationing and to study what vacationers actually do and experience during vacation." Thus, in the present study we aim to close this gap by examining what kinds of experiences people have on a given vacation day, and how these experiences might contribute to recovery from accumulated strain. Taking a novel, holistic approach to recovery, we integrate two distinct strands of literature (i.e., recovery from work and motivational approaches to recovery), which we will introduce in turn next.

Recovery from Work

In their influential work on recovery, Sonnentag and Fritz (2007) introduced the Recovery Experience Questionnaire assessing four factors contributing to recovery. Focusing on the interplay between work and leisure, the authors posit that *psychological detachment* (i.e., the process of "switching off" from daily stressors and forgetting about them), *relaxation* (i.e., a state of low sympathetic arousal), *mastery* (i.e., the feelings of success or achievement that result from prevailing in challenging situations), and *control* (i.e., the experience of deciding for oneself what to do during the day and how to do it) play a prominent role in recovering from work. Drawing on conservation of resources (COR, Hobfoll, 1989) and effort–recovery theory (Meijman & Mulder, 1998), the authors conceptualize recovery as the process of reducing or eliminating physiological and mental strain reactions due to high job demands and stressful events at work (Sonnentag & Fritz, 2015).

Importantly, the authors argue that "it is not primarily the acute stress reaction that is detrimental for an organism but rather the sustained activation, even when the stressor is no longer present" (Sonnentag & Fritz, 2015, p. 75). Thus, in order to successfully recover from accumulated strain, it is essential for people to experience psychological detachment, relaxation, mastery, and control during leisure. Empirical studies support this notion: People who experience more psychological detachment, relaxation, mastery, and control during leisure feel better, are more satisfied with their lives, and report less work-family conflict (Sonnentag et al., 2017). The more people detach from work in the evening, the better their mood at bedtime and the more recovered they feel the following morning (Sonnentag et al., 2017). In their more recent stressor-detachment model, Sonnentag and Fritz (2015) single out psychological detachment as the primary prerequisite of recovery: Encountering high levels of stressors at work (e.g., time pressure and workload) leads to less effective psychological detachment during leisure, which in turn leads to more accumulated strain, making recovery increasingly difficult (Sonnentag & Fritz, 2015).

Most of the research on recovery focuses on short-term processes after work. Only little is known about how detachment relates to recovery during longer periods of leisure such as a vacation. Given that work stressors are mostly absent during a vacation, one might wonder if psychological detachment is as effective a strategy for recovery during vacations as it is on the evenings of a work day. In fact, empirical evidence suggests that people who experienced more relaxation and control but, importantly, not more psychological detachment during their summer vacations also reported a steeper increase in health and well-being (De Bloom et al., 2013; but see Syrek et al., 2018). Thus, feeling relaxed and in control during vacations might be most important for enabling recovery in the vacation context.

A Motivational Perspective on Recovery

Anecdotally, one often hears that people need a certain amount of time during their vacations until the process of recovery even starts. During this time, detachment might be particularly important and, once detachment is achieved, people might feel that they truly start to recover and do not only counteract the accumulated work-related strain. The notion that some kind of "pre-recovery" period is necessary before the actual recovery process starts seems somewhat odd as this phase would seem to be part of the recovery process. However, it seems that people do not yet perceive to be recovering during this "pre-recovery" period. This leads to the question of how people determine when they are recovered.

We (Cardini & Freund, 2019a) recently proposed that a person's *mood*, *opportunity costs* (i.e., the perceived costs of forgoing attractive alternatives vs. the benefits of staying engaged in the focal activity), and *subjective time perception* experienced during an ongoing activity provide the person with valuable information about her current state of exhaustion and recovery. Drawing on the affect-as-cognitive-feedback account (Huntsinger et al., 2014), the opportunity cost model of subjective effort (Kurzban et al., 2013), and the time-as-information approach (Zakay, 2014), we argued that people perceive their current environment as contributing to their recovery when they are in a good mood, experience no opportunity costs and an accelerated sense of time. This pleasant state is thought to reflect a favorable cost-benefit ratio of the current environment (i.e., the perceived benefits outweigh the perceived costs; Inzlicht et al., 2014; Kool, Shenhav, & Botvinick, 2017), and incentivizes the person to stay engaged in the current activity. Conversely, once the cost-benefit ratio of the current environment turns unfavorable, a gradual decrease in mood, increase in opportunity costs, and expansion of the sense of time ensues. This progressively aversive state, in turn, is experienced by the person as exhaustion and incentivizes the person to disengage from the focal activity (see also van der Linden, 2011).

In our view, this approach to exhaustion and recovery is valuable for three reasons: First, it dispels the notion that exhaustion and recovery are mere processes of resource depletion and restoration (e.g., Kaplan & Berman, 2010; Muraven & Baumeister, 2000; Ryan & Deci, 2008), which has recently come under scrutiny (Carter et al., 2015). Instead, it aligns itself with more promising motivational models of exhaustion (e.g., Hockey, 2013; Inzlicht et al., 2014; Kurzban et al., 2013). Second, it substantially extends these models of exhaustion by bringing into the equation its counterpart – recovery. Third, it provides an explanation for what Inzlicht et al. (2018) have termed the "effort paradox" (i.e., why exerting effort is sometimes perceived as pleasant, despite an apparent general consensus that effort is aversive; Kurzban, 2016; Shenhav et al., 2017): When spending effort on a task is inherently valuable to a person or is expected to lead to valued outcomes, then effort is weighed as a benefit towards the cost-benefit ratio of said task, thus generating a pleasant state and shielding the person from the aversive state that non-valued effort would otherwise effectuate (i.e., when it is weighed as a cost towards the cost-benefit ratio).

Applied to the vacation context, the model predicts that when a person evaluates to what extent the concluding vacation day has contributed to her recovery, she will take into account how good or bad the day has made her feel (daily mood), how attractive it would have been for her to spend the day differently (daily opportunity costs), and how quickly or slowly she perceived the day to have passed (daily time perception). The current study was designed to test these hypotheses.

The Present Study

The present study expands previous work on recovery in three substantial ways. First, we aimed to investigate the motivational model of recovery (Cardini & Freund, 2019a) by examining the role of daily mood, opportunity costs, and subjective time perception for recovery in the vacation context. To gauge the value of the model's contribution to our understanding of recovery, we included as covariates other well-established factors influencing recovery (i.e., daily psychological detachment, relaxation, mastery, and control; Sonnentag & Fritz, 2007). Doing so allowed us to compare the relative importance between these experiences for explaining daily fluctuations in recovery. Second, we used a daily diary design of 21 consecutive days, starting on the first day of vacation. This intensive short-term longitudinal design allowed us to model how recovery and related experiences unfold in a naturalistic recovery setting (i.e., students' summer break after the demanding exam period). We chose this recovery setting because university students typically report high levels of exhaustion at the end of an academic semester and being in need of a vacation (e.g., Law, 2007; Schaufeli, Martinez, Pinto, Salanova, & Bakker, 2002). Third, in addition to assessing subjective recovery, we included a measure of people's perceived closeness to their optimal recovery on any given day. This allowed us to distinguish between daily fluctuations in recovery and longer-term progress towards one's aspired recovery level. While we expected both measures to be closely associated (i.e., people should perceive themselves closer to their optimal recovery on a day when they also feel more recovered), we were primarily interested in examining whether people weigh their daily experiences differently towards their assessments of daily recovery and longer-term recovery progress.

Based on the potential of vacations to enhance people's health and well-being (e.g., De Bloom et al., 2009), we hypothesized that daily recovery and proximity to the aspired recovery level increase over the course of the vacation. Furthermore, we hypothesized that daily mood and time perception are positively, and opportunity costs negatively associated with daily recovery, and that out of these three indicators, mood shows the strongest association with recovery (Cardini & Freund, 2019b). Furthermore, the same general pattern should hold for daily evaluations of optimal recovery proximity: According to feedback control models of self-regulation, positive mood signals a faster-than-expected progress towards one's goal (Carver & Scheier, 2004). It follows that a person should feel closer to her goal of optimal recovery when she's in a good mood on a given day. Finally, we explored the relative importance between the psychological indicators we have proposed (Cardini & Freund, 2019a) and the factors identified by Sonnentag and Fritz (2007) for explaining daily fluctuations in recovery.

Method

Participants

Students were recruited via mailing lists, online advertisements, and posters at different universities in Switzerland, Germany, and Austria. Students were eligible for participation if they intended to take a break from their studies and work for at least two weeks after the last exam. The recruitment advertisement included a link to an online screening questionnaire programmed with SoSci Survey (www.soscisurvey.de). Based on power simulations by Bolger and Laurenceau (2013) for estimating within-person relationships in daily diary designs, we aimed for a sample of at least 120 participants. Because we suspected that a substantial number of participants might drop out of a study taking place during their vacation, we recruited an initial sample of $N = 176$ students who filled out the online screening and signed up to receive the daily questionnaires. Of those, $n = 21$ did not fill out any and $n = 8$ only filled out one daily questionnaire; they were excluded from further analyses. The excluded subsample did not differ substantially from the rest on various trait measures (e.g., age, gender, recovery, exhaustion, and mood; *p*s between .20 and .95). The final sample consisted of $N = 147$ undergraduate students ($M = 24.14$ years, $SD = 3.88$; 85% women) from the fields of psychology (58%), medicine (20%), or law (5%).

Procedure

After giving informed consent, participants provided sociodemographic information and reported on various dispositional variables (e.g., exhaustion, recovery, mood, wakefulness, and calmness). They then rated their degree of recovery, exhaustion, mood, time perception, and opportunity costs with respect to the concluding academic semester and estimated how many days they would need to fully recover from it ($M = 10.91$ days, $SD = 9.43$, range = 0-60). Finally, they indicated the date of their last exam and whether they had planned to stay at home (61%) or go on vacation (39%) in their summer break. On average, students filled out the online screening 19.57 days ($SD = 20.14$) before their last exam. A small number of students ($n = 10$) filled out the screening two to eight days after their last exam. All other participants started the diary part the day after their last exam. They were asked to fill out a daily questionnaire on their smartphones for 21 consecutive days. The questionnaires were sent out each day at five p.m. via SMS or email prompts.

The daily questionnaires assessed students' daily recovery, mood, time perception, opportunity costs, distance to their optimal recovery, detachment, relaxation, mastery, control, and activities. The item presentation order was randomized. To prevent participants' end-of-day tiredness from influencing their daily ratings, we only considered questionnaires that were completed between the "downtime" of five p.m. and 7:30 p.m. (N = 2342). We incentivized adherence to this time window by giving students one raffle ticket for every timely submitted questionnaire. The raffle took place at the end of the study (15 x 20, 10 x 50, 5 x 100 Swiss francs or Euros). We excluded 63 questionnaires that were completed before five p.m. and 229 after 7:30 p.m. On average, students filled out 17.32 valid questionnaires (SD = 3.61, range: 2-21). At the end of the study, all students received personalized feedback on their recovery time course and related experiences, were debriefed, and notified if they had won at the raffle.

Measures

Dispositional exhaustion and recovery. The General Exhaustion and Recovery Scale (Cardini et al., 2019) measures dispositional exhaustion and recovery as two separate dimensions. The exhaustion dimension consists of 8 items (e.g., "*In general, I feel weak*"; α = .88). The recovery dimension consists of 5 items (e.g., "*In general, I feel energized*"; α = .81). Items were measured on a scale from 0 (*not at all*) to 5 (*very much*). The means, standard deviations, and correlations between the study variables are depicted in Table 8.

Table 8

Means, Standard Deviations, and Zero-Order Correlations Between Dispositional and Daily Measures.

Measure	*M* (*SD*)	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Trait recovery	2.63 (0.90)	–												
2. Trait exhaustion	1.79 (1.00)	-.73	–											
3. Trait wakefulness	2.42 (1.05)	.61	-.69	–										
4. Trait good mood	3.43 (0.97)	.62	-.77	.72	–									
5. Trait calmness	2.53 (1.14)	.50	-.62	.65	.70	–								
6. Daily recovery	0.57 (2.68)	.09	-.21	.32	.31	.19	–							
7. Daily goal proximity	0.85 (2.59)	.14	-.28	.29	.30	.24	.78	–						
8. Daily mood	2.04 (2.28)	.23	-.31	.27	.42	.19	.66	.62	–					
9. Daily opportunity costs	-1.24 (2.99)	-.19	.29	-.21	-.30	-.23	-.45	-.41	-.60	–				
10. Daily time perception	1.51 (2.56)	.10	-.17	.21	.24	.12	.47	.39	.54	-.41	–			
11. Daily detachment	2.89 (1.71)	.18	-.23	.25	.31	.26	.54	.45	.54	-.53	.36	–		
12. Daily relaxation	2.90 (1.51)	.19	-.21	.26	.31	.22	.66	.54	.60	-.59	.41	.69	–	
13. Daily mastery	1.62 (1.42)	.20	-.16	.16	.07	.09	.06	.14	.06	.06	-.06	-.02	.00	–
14. Daily control	3.38 (1.41)	.28	-.34	.31	.39	.19	.61	.55	.71	-.66	.50	.59	.75	.10

Note. *N* = 147 persons, 21 days, 2,332-2,342 observations. Daily measures are aggregated across persons and measurement occasions. The critical correlation coefficient for a significance level of α = .05 (two-tailed) is .16

Dispositional mood state. The Multidimensional Mood State Questionnaire (German short version; Steyer et al., 1997) measures three bipolar dimensions of psychological functioning: Wakefulness (vs. tiredness; 4 items, $\alpha = .86$), good mood (vs. bad mood; 4 items, $\alpha = .87$), and calmness (vs. nervousness; 4 items, $\alpha = .89$) on a scale from 0 (*not at all*) to 5 (*very much*).

Daily recovery and optimal recovery proximity. The dependent variables were: (1) Daily recovery ("*How much has this day exhausted or recovered you?*") measured on a bipolar visual analogue scale ranging from -5 (*very exhausted*) to +5 (*very recovered*), and (2) daily optimal recovery proximity ("*How far away from or close to your optimal recovery are you today?*") with -5 (*very far away*) to +5 (*very close*). Within-person reliabilities were good (R_{Cn} of .87 for recovery and .86 for optimal recovery proximity; Cranford et al., 2006), indicating that these items are sensitive to detecting interindividual differences in intraindividual variability.

Daily psychological indicators of recovery. To examine and compare the effects of the psychological indicators of recovery (Cardini & Freund, 2019a) on daily recovery and optimal recovery proximity, we modeled each as a time-varying independent variable. We assessed daily mood with the item "*How was your mood today?*" on a bipolar visual analogue scale ranging from -5 (*very bad*) to +5 (*very good*), daily opportunity costs with "*Would you have preferred to do something different today?*" with -5 (*not at all*) to +5 (*something completely different*), and daily time perception with "*How slowly or fast did this day pass?*" with -5 (*very slowly*) to +5 (*very fast*). Within-person reliabilities were good (R_{Cn}s of .86 for mood and time perception and .87 for opportunity costs).

Daily experiences influencing recovery. To assess as time-varying covariates the four previously identified factors impacting recovery, for each factor we used the item with the highest factor loading as reported by Sonnentag and Fritz (2007): (1) Psychological detachment ("*Today I forgot about work*"), (2) relaxation ("*Today I kicked back and relaxed*"), (3) mastery ("*Today I sought out intellectual challenges*"), and (4) control ("*Today I felt like I could decide for myself what to do*"). Items were measured on a Likert scale ranging from 0 (*not at all*) to 5 (*a lot*). Within-person reliabilities were good (all R_{Cn}s = .86).

Daily activities. At each measurement occasion, students indicated if they had been engaged in one or more of the following activities during the day: Sports (n = 489), relaxation (n = 1210), friends and family (n = 1347), culture (n = 267), work (n = 637), and other (n = 726). On average, students were engaged in 1.99 activities per day (SD = 0.60).

Statistical Analysis

We followed the suggestions of Bolger and Laurenceau (2013) for reporting multilevel analyses. In a first step, we analyzed the time courses of the daily measures using unconditional multilevel growth curve models with measurement occasion (21 days, coded from 0 to 20, such that 0 indicates the first day after the last exam) as the sole independent variable, allowing for a simple autocorrelative error structure (AR[1]) and, where applicable, accounting for heteroscedasticity of the measures over time. In a second step, we extended these analyses to conditional multilevel growth curve models. This allowed us to estimate and compare the extent to which the psychological indicators of recovery (i.e., mood, opportunity costs, time perception) are associated with both daily recovery and optimal recovery proximity, while controlling for important time-varying covariates (i.e., psychological detachment, relaxation, mastery, and control).

Importantly, because these daily measures varied both between and within persons and we were primarily interested in the estimation of within-person associations, we disaggregated these variables into their respective between- and within-person components, taking into account the unbalanced design of the data and the variables' relationship with time. Specifically, we used the traditional approach (i.e., person-mean centering) only when the variable was unrelated to time. If a variable was systematically related to time, we instead used the detrending approach (Curran & Bauer, 2011) by first regressing the variable on time separately for each person using ordinary least squares and then subtracting the raw values for each person at each measurement occasion from the model-implied slope value at that occasion (i.e., retaining the time-specific residuals from the regression). A positive regression coefficient of the between-person component of an independent variable can be interpreted as follows: Students with higher average values of the independent variable (across all days) also tend to have higher average values of the dependent variable (across all days). A positive regression coefficient of the within-person component of an independent variable can be interpreted as follows: Students who report higher than usual values of the independent variable (on a specific day) also tend to report higher than usual values of the dependent variable (on that specific day).

We conducted all analyses in R (R Core Team, 2018). For the time course analyses, we used the nlme package (Pinheiro et al., 2018). For the time–varying covariates analyses, we used the Bayesian brms package (Bürkner, 2017), as this package tends to converge more reliably for multilevel models with complex variance-covariance matrices.

Results

The initial multilevel analysis dataset consisted of 2,342 observations. Inspection of the scatterplots, person by person, indicated that due to a very infrequent technical failure, two persons had missing data for one measurement occasion for optimal recovery proximity and eight persons had missing data for one measurement occasion for psychological detachment, relaxation, mastery, and control. Thus, we conducted the following analyses on a total ranging between 2,332 and 2,342 observations.

Modeling the Time Courses

Model building. All daily measures showed substantial between-person variance (ICCs between .18 and .36), confirming the nested structure of the data (days nested in students) and necessitating the use of multilevel modeling. We began the model building process by comparing the ordinary least squares null model to a random-intercept null model for the daily measures. Given that these models are nested, we decided on the better-fitting model using the chi-square likelihood ratio test under restricted maximum likelihood estimation. The random-intercept model fit the data better in all instances, indicating that students differed in their initial intercepts (i.e., the day after the last exam) on all daily measures.

We then added time as a single fixed effect independent variable in the models. Since the models with time were not nested in the random-intercept model (i.e., had a different fixed effect structure), we decided on the better fitting model using the AIC and BIC under full maximum likelihood estimation, with lower values indicating better model fit. The model with linear time as independent variable fit the data better for daily recovery, optimal recovery proximity, psychological detachment, and mastery (the model including a quadratic fixed effect of time fit the data worse in all instances). Thus, students on average reported systematic linear changes in these variables across the study period.

In a next step, we added a random slope for time to the models, comparing them to the prior models using chi square likelihood ratio tests. These models fit the data better in all instances except for time perception, indicating that students differed with regard to their individual time courses for every daily measure except time perception.

As a last step, we added a simple autocorrelative error structure (AR[1]) to the models and tested whether they should account for heteroscedasticity. The models accounting for autocorrelation but not for heteroscedasticity fit the data better in all instances.

The final models for each daily measure are depicted in Figure 6, which visualizes the time courses using two sets of parameter estimates. The first set, the fixed effects of time, estimate the time courses for the average student in the sample. These fixed effects are represented by the thick black lines. The second set are the between-person random effects of time, which estimate the extent to which the time courses of single students deviate from the time course of the typical student in the sample. These random effects are represented by the variability in individual regression lines (thin grey lines) from the average regression line.

Fixed effects of time. As expected, both daily recovery and daily optimal recovery proximity increased on average during the vacation, $b = 0.04$, $SE = 0.01$, 95% CI [0.02, 0.07] and $b = 0.09$, $SE = 0.01$, 95% CI [0.06, 0.11], respectively. Daily mood, opportunity costs, and time perception did not systematically change over time. Daily psychological detachment and mastery slightly increased, $b = 0.02$, $SE = 0.01$, 95% CI [0.01, 0.04] and $b = 0.02$, $SE = 0.01$, 95% CI [0.01, 0.03], respectively, while relaxation and control remained constant.

Random effects of time. As can be seen in Figure 6, all daily measures showed substantial between-person variability in intercepts and slopes (except for time perception, which showed no variability in slopes). The variation in intercepts of the daily measures ranged between 0.65 and 1.92 standard deviations, meaning that approximately 68% of the model-implied individual intercepts were located within ±0.65 up to ±1.92 units from the average initial intercepts. In addition, approximately 68% of the model-implied individual slopes for time were located within ±0.03 up to ±0.11 units from the average slopes. The within-person variability (i.e., the residuals of the individual regression lines) ranged between 1.11 and 2.69 standard deviations. This means that, across time and students, approximately 68% of the raw data points deviated ±1.11 up to ±2.69 units from the model-implied individual regression lines.

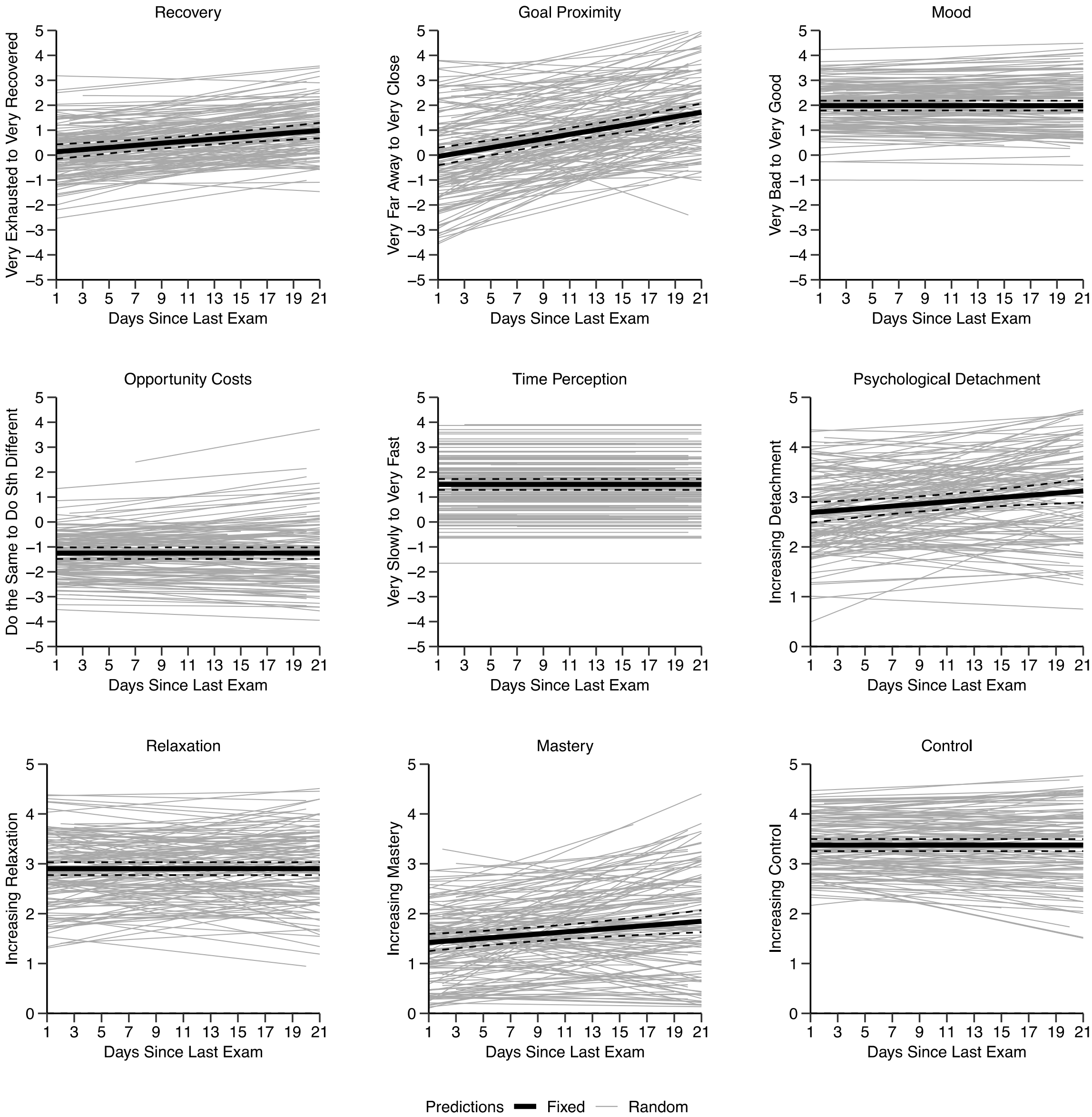

Figure 6. Spaghetti plots of the fixed and random effects of time for the daily measures. Dashed lines represent 95% confidence intervals for the fixed effects.

Main Analyses

To test the hypothesis that daily mood and time perception are positively and opportunity costs negatively related to daily recovery and optimal recovery proximity, we ran four Bayesian multilevel models. We first estimated the sole impact of daily mood, opportunity costs, and time perception on daily recovery and optimal recovery proximity, without controlling for other factors (Baseline Models in Table 9). Next, we included daily detachment, relaxation, mastery, and control as time-varying covariates in the models (Covariates Models in Table 9).

The left part of Table 9 summarizes the multilevel models for daily recovery as a function of the psychological indicators of recovery and other factors, controlling for time. As can be seen, daily mood, opportunity costs, and time perception independently explained variance in daily recovery, albeit with varying strength. As expected, daily mood had the strongest impact on daily recovery, $b = 0.35$, $SE = 0.03$, 95% CI [0.28, 0.41], followed by opportunity costs, $b = -0.21$, $SE = 0.03$, 95% CI [-0.26, -0.16]. In comparison, daily time perception was only weakly associated with daily recovery, $b = 0.08$, $SE = 0.03$, 95% CI [0.02, 0.14]. Thus, on days when people reported better mood, lower opportunity costs, and faster time perception than usual, they also tended to report higher levels of recovery than usual. Importantly, these relationships remained substantial even after we included the other factors as further time-varying covariates in the model. Only relaxation ($b = 0.61$, $SE = 0.06$, 95% CI [0.49, 0.74]) and control ($b = 0.12$, $SE = 0.06$, 95% CI [0.01, 0.24]) uniquely explained variance in daily recovery.

The right part of Table 9 summarizes the multilevel models for daily optimal recovery proximity. Again, daily mood, opportunity costs, and time perception independently explained variance in daily optimal recovery proximity, with daily mood showing the strongest association ($b = 0.19$, $SE = 0.01$, 95% CI [0.14, 0.24]), followed by opportunity costs ($b = -0.12$, $SE = 0.02$, 95% CI [-0.15, -0.08]), and time perception showing a comparably weak association ($b = 0.04$, $SE = 0.02$, 95% CI [0.005, 0.07]). However, unlike daily recovery, time perception did not explain unique variance in recovery in the Covariates Model anymore, $b = 0.03$, $SE = 0.02$, 95% CI [-0.004, 0.06]. As expected, out of all the covariates, daily recovery showed the strongest association with optimal recovery proximity.

Table 9

Bayesian Multilevel Model Estimates for Daily Recovery and Optimal Recovery Proximity as a Function of Daily Mood, Opportunity Costs, Time Perception, Psychological Detachment, Relaxation, Mastery, and Control.

	Daily Recovery								Daily Optimal Recovery Proximity							
	Baseline Model				Covariates Model				Baseline Model				Covariates Model			
			95% CI				95% CI				95% CI				95% CI	
Predictors	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper
Fixed Effects																
Intercept	-0.48	0.15	-0.77	-0.19	-2.59	0.40	-3.37	-1.80	-0.05	0.21	-0.45	0.37	-1.93	0.49	-2.91	-0.98
Time	0.05	0.01	0.02	0.07	0.05	0.01	0.03	0.07	0.09	0.01	0.07	0.12	0.09	0.01	0.07	0.12
Mood	0.35	0.03	0.28	0.41	0.24	0.04	0.17	0.31	0.19	0.03	0.14	0.24	0.16	0.03	0.11	0.21
Opportunity Costs	-0.21	0.03	-0.26	-0.16	-0.08	0.02	-0.13	-0.03	-0.12	0.02	-0.15	-0.08	-0.09	0.02	-0.12	-0.06
Time Perception	0.08	0.03	0.02	0.14	0.08	0.03	0.02	0.13	0.04	0.02	0.00	0.07	0.03	0.02	-0.00	0.06
Detachment	-	-	-	-	0.01	0.04	-0.08	0.09	-	-	-	-	0.07	0.03	0.01	0.13
Relaxation	-	-	-	-	0.61	0.06	0.49	0.74	-	-	-	-	0.16	0.04	0.08	0.23
Mastery	-	-	-	-	0.06	0.05	-0.03	0.15	-	-	-	-	0.08	0.03	0.02	0.14
Control	-	-	-	-	0.12	0.06	0.01	0.24	-	-	-	-	0.09	0.04	0.02	0.17
Recovery	-	-	-	-	-	-	-	-	0.35	0.02	0.30	0.39	0.30	0.02	0.25	0.34

Table 9 (continued)

	Daily Recovery								Daily Optimal Recovery Proximity							
	Baseline Model				Covariates Model				Baseline Model				Covariates Model			
			95% CI				95% CI				95% CI				95% CI	
Predictors	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper
Random Effects																
Intercept	0.85	0.08	0.70	1.00	0.77	0.07	0.64	0.92	1.21	0.09	1.04	1.40	1.07	0.08	0.93	1.23
Time	0.10	0.01	0.07	0.12	0.10	0.01	0.07	0.12	0.16	0.01	0.13	0.18	0.15	0.01	0.12	0.17
Residual	1.96	0.03	1.90	2.03	1.75	0.03	1.69	1.82	1.22	0.02	1.18	1.27	1.13	0.02	1.09	1.18
AR(1)	0.08	0.03	0.03	0.14	0.09	0.03	0.03	0.15	0.12	0.03	0.06	0.18	0.08	0.03	0.02	0.14
LOO–IC	10168	77.20	-	-	9236	80.00	-	-	8190	105.10	-	-	7561	96.30	-	-
Marginal R^2	.28				.40				.42				.51			
Conditional R^2	.43				.57				.77				.80			

Note. N = 147 persons, 21 days, 2,332-2,342 observations. Est = Estimate. Depicted are the unstandardized regression coefficients for the within-person fixed effects and the standard deviations and correlations for the random effects. LOO–IC = Approximate leave-one-out cross-validation information criterion based on the posterior likelihood (smaller values indicate better model fit). Marginal R^2 depicts the proportion of variance explained by the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined. Time is mean-centered (0 represents day 10 after the final exam). The default priors of the brms R-package (Bürkner, 2017) were used. Depicted are the within-person fixed effects (the between-person fixed effects and within-person random effects were included in the analyses; see Table A10 in Appendix A for the full table containing all model parameters).

Discussion

This extensive daily diary study tracking students' recovery experiences during a vacation demonstrates that daily mood, opportunity costs, and – to a lesser degree – subjective time perception independently contribute to fluctuations in daily recovery: People felt more recovered on days when they were in a better-than-usual mood, experienced less-than-usual opportunity costs, and perceived the day to have passed more quickly than usual. Crucially, these associations held even when controlling for the passage of time and other well-established factors influencing recovery, namely psychological detachment, relaxation, mastery, and control (Sonnentag & Fritz, 2007). These results provide empirical support for the motivational model of recovery in the context of a vacation (Cardini & Freund, 2019a). Feeling relaxed and in control of the daily program, while important factors for recovery in and of themselves, are not sufficient to explain daily fluctuations in recovery during a vacation. This study has demonstrated that additional affective (i.e., mood) and cognitive (i.e., opportunity costs) indicators of recovery need to be considered to paint a clearer picture of the recovery process. This finding is in line with other research demonstrating that savoring and deriving pleasure from leisure activities can contribute to one's health and well-being during a vacation (De Bloom et al., 2013).

Increasing the Recovery Potential of Vacations

Given that people report being more recovered on days when they are in a better mood, the question arises as to which strategies they can employ to enhance their mood on a given vacation day. Research on mood regulation suggests that exercising, listening to music, and engaging in meaningful social interactions play an important role in elevating one's mood (Thayer et al., 1994). Thus, creating opportunities to meet other people (e.g., going out with friends or traveling), sticking to one's workout routine, and frequently listening to one's favorite songs might prove beneficial for recovery in the vacation context. Supporting this notion, more than half of the mentioned daily activities in the present study related to social interactions (58%), and one in five of them related to physical exercise (21%). Prior empirical research has also demonstrated that physical exercise can be beneficial for recovery (e.g., Rook & Zijlstra, 2006). Interestingly, it seems that mood *moderates* the relationship between physical activity and recovery: The amount of time spent on physical activities after work is positively related to recovery at bedtime only when people report being happy during these activities (Oerlemans, Bakker, & Demerouti, 2014). Furthermore, in addition to enhancing one's mood, listening to music might also induce a state of relaxation by facilitating the deactivation of the sympathetic nervous system (Finn & Fancourt, 2018), hence contributing to recovery in more than one way.

Research on the experience of *flow* (Csikszentmihalyi, 1975) demonstrates that people thrive in environments that contain high opportunities for action (i.e., perceived challenges), are matched with people's own capacities to act (i.e., perceived skills), and provide frequent feedback about one's progress. Be it work or leisure: The more people are approximating the conditions of flow in a given situation, the more they perceive the situation as pleasant (e.g., Csikszentmihalyi & LeFevre, 1989). Thus, engaging in challenging, yet manageable activities that foster the monitoring of one's progress towards a goal might constitute another pathway to happiness throughout a vacation day. On a related note, frequent monitoring of one's goal progress enhances the likelihood of goal attainment (Harkin et al., 2016), which should further contribute to positive mood.

A critical question given the high correlation of positive mood and recovery is if they represent the same construct. Feeling recovered might be an important aspect of positive mood, and feeling exhausted might be an aspect of negative mood. Note, however, that a strong correlation does not imply the identity of a construct. We (Cardini & Freund, 2019a) maintain that the process of recovery from exhaustion leads to an increase in positive mood.

However, there are many other variables contributing to a good mood that might not directly influence the recovery process (e.g., good weather, spending time with a good friend, etc.). Similarly, one can easily think of situations in which one is exhausted yet in a good mood (e.g., after having finished a marathon or a difficult exam). Thus, positive mood and recovery are theoretically – and empirically - related yet denote different psychological constructs.

Given that experiencing opportunity costs is negatively related to daily recovery: How can people keep daily opportunity costs at a low level? *Planning* one's vacation day in advance might prove an effective strategy. Put simply, planning facilitates daily goal pursuit because it helps people to stay committed to their goals in the face of distractions, obstacles, and setbacks (Gollwitzer & Sheeran, 2006). Achieving more of one's daily goals, in turn, will likely lead to more positive evaluations of that day (e.g., "Today was a great day because I have done what I set out to do"), thereby reducing thoughts about how the day could have been spent in a better way. In addition, planning might also contribute to recovery through enhancing the feeling of being in control of the daily program, which was positively related to daily recovery in our study.

Limitations

This study has at least three limitations. First, retrospective biases cannot be completely ruled out with the current daily diary design. For instance, when asked to rate their mood on a given day, it is not clear if the answer reflects persons' averaged evaluations of their mood on that day up to the time of testing, or if it reflects one or more particularly salient mood states that they experienced on that day (e.g., peak-end heuristic; Kahneman, Frederickson, Schreiber, & Redelmeier, 1993). We tried to address this issue by framing our items so that they encourage an accumulated evaluation of one's daily experiences, which most closely captures normative experiences (Miron-Shatz, 2009).

Second, to achieve an acceptable trade-off between brevity and complexity of the daily questionnaires, we relied on single-item measures of the daily variables. We reasoned that people probably do not like to be bothered with lengthy questionnaires when on vacation. However, everything else being equal, single-item measures have worse psychometric properties than multi-item measures. Despite this, the use of single-item measures also has its merits, especially so in daily diary designs and particularly when used during a vacation when people do not want to be bothered by having to fill out lengthy questionnaires, because it minimizes respondent burden, reduces criterion contamination (i.e., uses less construct-irrelevant and more clearly worded, easy-to-understand items), and enhances face validity (Fischer, Matthews, & Gibbons, 2016). Supporting this notion, single-item measures have been shown to be appropriate for assessing various constructs such as global life satisfaction (Cheung & Lucas, 2014), self-esteem (Robins, Hendin, & Trzesniewski, 2001), quality of life (De Boer et al., 2004), and job satisfaction (Wanous, Reichers, & Hudy, 1997). Furthermore, in the current study, we found that the daily single-item measures are precise in detecting interindividual differences in intraindividual variability (R_{Cn}s between .86 and .87; Cranford et al., 2006).

Third, we cannot rule out the possibility of inflated correlations due to common method variance (i.e., variance that is due to the measurement method rather than due to the constructs the measures represent; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Anticipating this problem, we took the following steps to try and reduce common method bias in the present study: (1) randomizing of the item presentation order, (2) varying of the item scale anchors of the predictor and criterion variables, (3) varying of the item scale formats of the predictor variables, (4) clear wording of the items.

Despite these limitations, to the authors’ knowledge, this daily diary study provides the as-yet most comprehensive insight into the dynamics of recovery during a vacation. Given that most biological and social processes are nonergodic (i.e., between-person differences do not always mirror within-person change over time; Molenaar & Campbell, 2009), by disaggregating within- and between-person variability in the daily measures, we were able to depict a more fine-grained picture of the within-person recovery process (Bolger & Laurenceau, 2013; Curran & Bauer, 2011). Furthermore, by collecting daily measurements from the first day of vacation for up to three weeks thereafter, we substantially expanded prior work investigating the temporal patterns of recovery over the course of a vacation (e.g., De Bloom et al., 2013; Nawijn, 2010; Syrek et al., 2018). Finally, the application of Bayesian multilevel analysis with the efficient brms R-package (Bürkner, 2017) allowed us to fully model the complex variance-covariance matrices of the multilevel regression models depicted in Table 2 (i.e., estimating all the random effects of the within-person independent variables). With this, we were able to increase the proportion of variance explained in daily recovery and to reduce time-specific residual variance.

Future Directions

As correlation does not allow causal inferences, experimental research is necessary to enhance our understanding of the causal antecedents and consequences of recovery during a vacation. However, we were unable to come up with an experimental design that allows for the manipulation of mood or opportunity costs during a vacation. To test the causal effect of mood and opportunity costs on recovery more directly, future studies could try to induce exhaustion and recovery in an experimental setting. Importantly, the experiment would need to include a manipulation of mood or opportunity costs between the exhaustion and recovery period. However, to prevent the manipulation from interfering with the recovery process, it would need to be very short. While we are less convinced of the possibility to manipulate mood in such a short amount of time, recent research has demonstrated efficient ways to manipulate opportunity costs (Cardini & Freund, 2019b; Hofmann et al., 2019).

A more realistic possible avenue for future field-based studies is to focus on more clearly distinguishing the temporal associations between recovery and its influencing factors. For instance, using an intensive experience sampling design, one could assess mood and opportunity costs multiple times throughout a day and recovery in the evening (preferably using multi-item and multi-method measures to further enhance their psychometric properties and reduce common method variance), which would enable the investigation of more directional relationships between the measures of interest.

Furthermore, it would be interesting to examine age-differential effects of daily mood and opportunity costs on recovery. For instance, given their increased focus on maintaining their current level of functioning and preventing further losses (e.g., Freund & Baltes, 2000), older adults might weigh daily opportunity costs more negatively towards their assessment of recovery (Cardini & Freund, 2019a). It seems to us that expanding the experience sampling design proposed above to include different age groups might be the best way forward in field research on recovery.

Conclusion

In accordance with Kuykendall et al. (2015), we found that recovery is not simply the result of elapsed time but also depends on the kinds of experiences people have on a given vacation day. Feeling relaxed and in control of the daily program – while in and of themselves important for recovery – might only be part of the story. This study identified positive mood and the absence of opportunity costs as important additional facilitators of daily recovery. Thus, filling one’s vacations with highly valued activities that contribute to one’s happiness and planning one’s vacation days in advance might be effective strategies to increase their recovery value.

PART V: DEVELOPMENT AND INITIAL VALIDATION OF A GENERAL EXHAUSTION AND RECOVERY SCALE

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This article has been submitted for publication (2019) in a peer-reviewed journal and is currently under review. Please do not copy or cite without permission of the authors.

Abstract

Most existing self-report measures depict exhaustion and recovery as opposite ends on a bipolar dimension. However, recent findings of only weak to moderate correlations between the constructs highlight the need for a scale that assesses exhaustion and recovery as separate factors. Based on existing questionnaires, we developed and validated a general Exhaustion and Recovery Scale in a series of three studies. We began by selecting items from established questionnaires that best represent the various functional domains in which exhaustion and recovery may occur (Study 1). The selected items showed excellent reliability and were best described by a correlated two-factor structure representing exhaustion and recovery (Study 2). The two-factor structure was cross-validated on an independent data set using confirmatory factor analysis (Study 3). Finally, the scale showed good concurrent validity (Study 4). Taken together, the Exhaustion and Recovery Scale is a psychometrically sound, easily administered, and brief self-report measure of momentary feelings of exhaustion and recovery.

Introduction

Everybody knows the feeling of exhaustion after a long day of being engaged in highly demanding tasks, and the associated need for recovery (e.g., Sonnentag & Zijlstra, 2006). Be it cognitively taxing work demands, physically tiring exercise routines, or emotionally draining encounters – *exhaustion* can arise from a variety of sources (Maslach & Jackson, 1981; Smets et al., 1995). Boksem and Tops (2008), focusing on *cognitive* exhaustion, define it as the feeling during or after a prolonged period of cognitive activity encompassing tiredness, an aversion to continue with the current activity, and a decrease in commitment to the activity at hand. Wright and Cropanzano (1997, p. 486) define *emotional* exhaustion as "a chronic state of physical and emotional depletion that results from excessive job demands and continuous hassles." Finally, taking a broader perspective, Smets and colleagues (1995, p. 315) define exhaustion as "a normal, everyday experience that most individuals report after inadequate sleep or rest, or after exertion of physical power," adding that cognitive effort can also contribute to exhaustion. Taken together, these definitions encompass multiple sources and expressions of exhaustion. Thus, we view exhaustion as a multi-faceted psychological construct comprising physical (e.g., increased tiredness), cognitive (e.g., aversive experience of effort), emotional (e.g., negative mood), motivational (e.g., reduced activity commitment), and behavioral (e.g., reduced activity performance) dimensions.

The counterpart of exhaustion is *recovery* and denotes the process of reducing or removing the feeling of exhaustion and its expression on different levels of functioning (Zijlstra & Sonnentag, 2006). In their effort-recovery model, Meijman and Mulder (1998) argue that recovery in one functional domain can only occur once a person ceases all effortful activities that contribute to that domain's exhaustion. For instance, a person is more likely to recover from one-hour of running by temporarily avoiding physically effortful activities. Similarly, a person dealing with cognitively taxing work demands may best unwind by engaging in activities that require no additional cognitive effort. Recuperating from these daily strains is important because it prevents the development of more harmful and chronic exhaustion states (Maslach & Jackson, 1981; Sonnentag & Fritz, 2007) or exercise-induced injuries (Järvinen et al., 2007).

How can one measure the multidimensionality of exhaustion and recovery? There are only few questionnaires that assess more than one dimension of these constructs (e.g., Demerouti, Bakker, Vardakou, & Kantas, 2003; Smets et al., 1995). Most existing self-report measures focus on one specific dimension of exhaustion and recovery. For example, the Maslach Burnout Inventory includes an emotional dimension of exhaustion that is used to assess levels of work-related stress (Maslach & Jackson, 1981). Moreover, most existing scales only measure either exhaustion or recovery but not both because of the underlying assumption that they constitute opposite poles on one bipolar dimension. However, this assumption conflicts with empirical findings of only small to moderate correlations between exhaustion and recovery, both at the state and trait level (e.g., Demerouti, Bakker, Sonnentag, & Fullagar, 2012). This suggests that exhaustion and recovery might be best measured as two separate (yet related) constructs. However, except for one questionnaire focusing exclusively on the work context (Winwood, Winefield, Dawson, & Lushington, 2005), to date no measure exists that includes exhaustion and recovery as separate constructs. This paper aims to close the gap by documenting the development and initial validation of a scale that includes exhaustion and recovery as separate dimensions. The main aim of this paper is to present a valid measure of exhaustion and recovery that can be applied to adults in various everyday life situations. For this purpose, we selected items with good psychometric properties of several well-established exhaustion and recovery questionnaires. In the next section, we will introduce the existing measures of exhaustion and recovery that served as the basis for the current studies.

Current Self-Report Measures of Exhaustion and Recovery

We identified seven questionnaires that are aimed at measuring exhaustion and recovery: There are two questionnaires that assess exhaustion and recovery relatively broadly, namely (1) the General Health Questionnaire (Goldberg & Hillier, 1979) that includes aspects of exhaustion in the form of loss of concentration, feelings of nervousness and unhappiness, failure to start a new activity, and depressive symptoms. Regarding recovery, it measures physical shape, mental alertness, affection for others, and the degree of happiness. (2) The Checklist Individual Strength (Vercoulen, Alberts, & Bleijenberg, 1999) provides a multidimensional assessment with measures of exhaustion severity, concentration, motivation, and physical activity level. Relevant recovery aspects are degree of activation, motivation to engage in pleasant activities, feeling rested, and one's physical shape.

We further selected three scales that measure work-related aspects of exhaustion and recovery: (3) The scale by Sonnentag and Kruel (2006) measures a person's state of recovery in the morning, distinguishing both physical and cognitive aspects. (4) The Need for Recovery Scale (Sluiter, 1999), developed to examine the short-term effects of a work day on a person's need for recovery, assesses work-related exhaustion. (5) The Utrecht Work Engagement Scale (Schaufeli, Salanova, González-Romá, & Bakker, 2002b) measures three recovery-related dimensions in the work context: vigor, dedication, and absorption. Here, recovery is formulated as persevering at work and resilience to high job demands.

Finally, there are two questionnaires that tap into more extreme cases of exhaustion. (6) The Maslach Burnout Inventory (Maslach & Jackson, 1981) measures severe emotional exhaustion. Note, however, that this measure only includes an emotional component of exhaustion stemming from stressful work demands, and does not necessarily translate into a person's physical or mental strains. The scale measures aspects of recovery such as feeling energetic, feeling exhilarated after working with customers, and being successful in dealing with emotional problems at work. (7) The Oldenburg Burnout Inventory (Demerouti et al., 2003) combines several dimensions of exhaustion: Here, exhaustion is further divided into physical, cognitive, and emotional components. Recovery aspects include successfully overcoming work pressures and having sufficient energy left after work.

Taken together, these scales provide measures for certain aspects of exhaustion and recovery that target different life contexts (e.g., work or leisure context). However, none of these scales provide a broad and general measure of both constructs that is applicable to a wide variety of situations in everyday life. To construct such a broad measure of exhaustion and recovery, we combined the items of the above described questionnaires, including items that target different functional levels of exhaustion and recovery (i.e., physical, cognitive, emotional, social, motivational, behavioral functional domains).

The Present Studies

In a series of four studies, we developed and provided initial validation of the Exhaustion and Recovery Scale. In Study 1, we searched the literature and selected exhaustion and recovery items from existing self-report measures. We then used a combination of classical item analysis, exploratory factor analysis, and a face validity procedure to select conceptually relevant items with good psychometric properties. In Study 2, we examined the selected items by assessing their reliability (internal consistency) and extracting their factor structure using exploratory factor analysis. In Study 3, we cross-validated the factor structure found in Study 2 on a new data set using confirmatory factor analysis. Exploring the factor structure of a set of items using exploratory factor analysis and subsequently validating this factor structure using confirmatory factor analysis on an independent data set is a generally accepted procedure of scale development and validation (e.g., Brown, 2015). Finally, in Study 4 we assessed the convergent and discriminant validity of the scale. For all studies, we followed the guidelines of the local ethics committee, including informed consent and debriefing of participants.

Study 1

We began by conducting a literature review with the aim of identifying relevant measures related to exhaustion and recovery. Out of these measures, we selected all items that are associated with the constructs of general exhaustion and recovery, and excluded domain-specific items. Items collected this way served as our initial item pool. To account for the multidimensionality of the constructs, we distinguished between several functional domains of exhaustion and recovery (i.e., physical, cognitive, emotional, social, and motivational exhaustion and recovery). We were interested in exploring whether persons differentiate between these functional domains in their subjective conceptualizations of exhaustion and recovery.

The aims of Study 1 were to (1) examine the item difficulties for the selected items, (2) convergence and differences between different functional domains of exhaustion and recovery, and (3) select those items that are representative of specific functional domains for further scale building.

Method

Participants. A total of N = 455 adults (44% female) aged between 18 and 72 years (M = 45.83, SD = 15.55) participated in this study. The sample was German speaking. We recruited the participants from an online access panel provided by a German research agency (Respondi AG). Participants from such panels are experienced in filling out online surveys and must adhere to severe guidelines aimed at producing and maintaining high quality responses. Participants were reimbursed according to the agency's regulations.

Materials and procedure. We programmed an online questionnaire with the software package SoSci Survey. We presented participants with a list of all the exhaustion and recovery items that we had previously identified in our literature review (see the eight instruments described above), which led to a pool of 47 exhaustion items and 36 recovery items.

To ensure consistency, we slightly reworded some items so that they captured momentary states of exhaustion and recovery. In addition, we presented each item five times; once for each functional domain of exhaustion and recovery that we had identified in the literature review (i.e., physical, cognitive, emotional, social, motivational). To familiarize participants with these different domains, we gave them specific everyday life examples (i.e., we told them that physical exhaustion can arise from a body workout, cognitive exhaustion can arise from a difficult concentration task, emotional exhaustion can arise from an intense argument with a partner, social exhaustion can arise after having spent a lot of time with other people, motivational exhaustion can arise after having resisted a temptation for a longer period of time). An example item for physical exhaustion was "*When I am physically exhausted, I feel burnt out*." A sample item for cognitive recovery was "*When I am cognitively recovered, I feel like doing all kinds of nice things*." Participants gave their responses on a 7-point scale ranging from 0 (*does not apply at all*) to 6 (*applies fully*). In addition, we asked participants to indicate the frequency with which they experience instances of physical, cognitive, emotional, social, and motivational exhaustion and recovery in their everyday lives on a scale of 0 (*never*) to 6 (*very often*).

Statistical analysis. We administered item and reliability analyses for each of the five functional domains of exhaustion and recovery. To reduce the number of items, we followed the criteria provided by Moosbrugger and Kelava (2012): We eliminated items with extreme item difficulties ($p < .15$ and $p > .85$) and weak item discriminations (corrected item-total correlation coefficients < .20). Furthermore, we eliminated items that, when excluded, yielded higher Cronbach's alpha coefficients (Cronbach, 1951).

Results and Discussion

Overall, most participants had experienced the different dimensions of exhaustion in their lives: 100% had encountered physical exhaustion, 98.4% cognitive exhaustion, 95.3% emotional exhaustion, 88.6% social exhaustion, and 86.4% motivational exhaustion. Physical exhaustion (M = 3.74, SD = 1.37), cognitive exhaustion (M = 3.24, SD = 1.59), motivational exhaustion (M = 3.11, SD = 1.66), and emotional exhaustion (M = 3.08, SD = 1.61) occurred fairly frequently in people's lives, but less frequently social exhaustion (M = 2.87, SD = 1.69).

Initial inspection of the data revealed satisfactory item difficulties for the exhaustion items, with all of them falling in the range of p > .15 and < .85. However, nearly all recovery items had difficulties higher than p = .85. This means that participants generally tended to endorse the recovery items. In addition, all exhaustion and recovery items had corrected item-total correlations of over .20. Thus, we could not remove any items based on the outlined criteria. Therefore, in a next step we ran five principal axis factor analyses with a forced one-factor solution for all functional domains of exhaustion and recovery, respectively. Our aim was to remove items with factor loadings under .40 for any of the functional domains. However, the analyses revealed that all item factor loadings exceeded the critical value of .40.

In summary, then, the results of this study did not allow us to reduce our initial item pool based on the criteria set by Moosbrugger and Kelava (2012). Therefore, in a next step we rated the items based on their face validity by consensus among the three authors of this paper. We classified each item to one functional domain of exhaustion and recovery. For example, we classified the exhaustion item "*Being with other people puts a strain on me*" as social, the item "*I have trouble concentrating*" as cognitive, the item "*I am in a bad mood*" as emotional. As an additional criterion, we only selected items that were suited equally well for trait and state measures. For example, the item "*I'm in a bad mood*" can be used as a general measure ("*In general…*") or as a situational measure of exhaustion ("*Right now…*"). Through this procedure, we selected 17 exhaustion and 9 recovery items (see Table 10).

Study 2

In the second study, we examined the reliability and factor structure of the exhaustion and recovery items selected in Study 1. In particular, we explored whether the selected items can be defined by a two-factor structure.

Method

Participants. A total of N = 119 adults (50% female) aged between 18 and 98 years (M = 48.81, SD = 17.88) participated in this study. Participants were recruited by the same research agency as in Study 1 with the inclusion criterion of not having participated in Study 1. Ten participants did not fill out the exhaustion and recovery items, and were therefore excluded from further analyses. The final sample size was N = 109 participants.

Materials and procedure. As part of a larger study unrelated to this manuscript, we included the exhaustion (n = 17) and recovery (n = 9) items selected in Study 1 in a state version. For each item, we asked participants to rate their current feelings on a 6-point scale ranging from 0 (*does not apply at all*) to 5 (*applies fully*). A sample item for exhaustion is "*Right now I feel tired*." A sample item for recovery is "*Right now I feel refreshed*."

Table 10

*Factor Loadings and Item Communalities for Study 2 (*N *= 104) and Study 3 (*N *= 180).*

	Study 2		Study 3	
Item	λ	R^2	β	R^2
Factor 1: Exhaustion				
1. I feel burned out	.87	.79	.83	.68
2. I feel like I'm at the end of my rope	.88	.74	.82	.68
3. I feel weak	.81	.78	.78	.60
4. I find everything getting on top of me	.90	.74	.74	.54
5. I'm in a bad mood	.83	.65	.66	.44
6. I feel sickened by everything	.91	.78	.74	.54
7. I feel nervous	.86	.68	Dropped	
8. I'm indifferent toward everything	.82	.65	.58	.33
9. I feel like doing nothing	.85	.72	.80	.64
10. Being with other people puts a strain on me	.80	.63	Items did not meet inclusion criterion of λ > .80	
11. I find it hard to show interest in other people	.78	.57		
12. People should leave me alone for some time	.79	.62		
13. It takes me longer to accomplish things	.79	.68		
14. I have trouble concentrating	.69	.63		
15. I'm too tired to start other activities	.76	.69		
16. I feel tired	.66	.65		
17. I feel no desire to do anything	.75	.55		

Table 10 (continued)

Item	Study 2 λ	Study 2 R^2	Study 3 β	Study 3 R^2
Factor 2: Recovery				
1. I feel energized	.91	.81	.86	.73
2. I feel refreshed	.88	.77	.80	.64
3. I feel that I'm doing things better than usual	.81	.60	.58	.34
4. I could tolerate the pressure very well	.84	.64	.60	.36
5. I could stay active for a long time	.82	.69	.77	.60
6. I feel rested	.72	.58	Items did not meet inclusion criterion of λ > .80	
7. I feel like doing all kinds of nice things	.46	.24		
8. I'm able to concentrate on what I'm doing	.75	.56		
9. I tend to persevere, even if things don't go well	.59	.40		
Factor correlation				
	$r = -.35$		$r = -.74$	

Note. λ = Pattern matrix factor loadings. β = Standardized factor loadings.

Parameter estimates for Study 2 are the result of a principal axis factor analysis with promax rotation and a forced two-factor solution. Parameter estimates for Study 3 are the result of a two-factor CFA based on robust maximum likelihood estimation with the Satorra-Bentler scaling correction, excluding exhaustion item 7 and including an error covariance between exhaustion items 5 and 6. The goodness-of-fit indices for this CFA model are reported in Table 11.

Statistical analysis. In this study, all exhaustion and recovery items were non-normally distributed, as assessed by Shapiro-Wilk tests (all *p*s < .01). Therefore, we followed the guidelines by Costello and Osborne (2005) for conducting exploratory factor analysis using principal axis factoring with a promax (oblique) rotation, allowing for the extracted factors to be correlated. We determined the most appropriate factor solution by combining the scree test (Cattell, 1966), the Kaiser-Guttman rule (i.e., keep factors with eigenvalues higher than one; Kaiser, 1991), parallel analysis (Horn, 1965), strength of parameter estimates (i.e., keep items with factor loadings > .80) and the general interpretability of the factors. In addition, we measured the internal consistency of the scales using the Cronbach's alpha correlation coefficient.

Results and Discussion

Both scales showed excellent reliability, with a Cronbach's alpha of .92 for the Recovery scale and .97 for the Exhaustion scale. Corrected item-total correlations ranged from .49 to .85 for the Recovery scale and from .73 to .88 for the Exhaustion scale.

A principal axis factor analysis with a promax rotation revealed a satisfactory Kaiser-Meyer-Olkin Measure of Sampling Adequacy of .91 and a statistically significant Bartlett's Test of Sphericity (*p* < .01). The factor analysis initially extracted three factors with eigenvalues higher than 1. However, an inspection of the scree plot of the eigenvalues (see Figure 1) revealed that the scree begins at the third factor, suggesting that only the first two factors should be retained. Thus, we re-analyzed the data by forcing a two-factor solution for the rotated principal axis factor analysis. The results provide evidence of factorial validity: The first extracted factor represents exhaustion and accounts for 49% of the variance. The second extracted factor represents recovery and accounts for 18% of the variance. Inspecting the pattern matrix revealed that some items fell short of loading higher than .80 on their

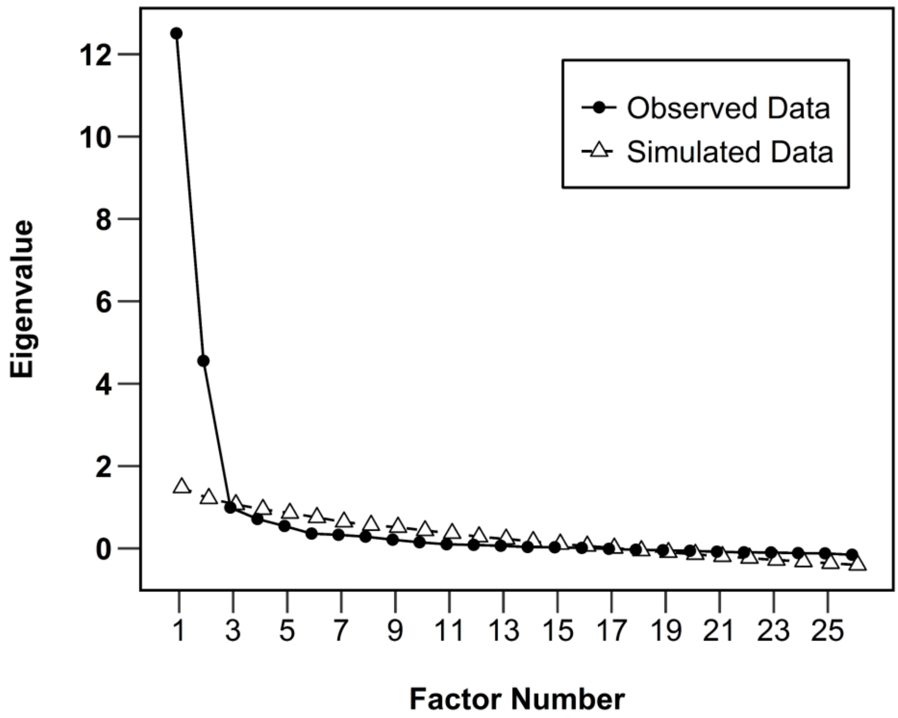

Figure 7. Scree plot of the eigenvalues for the principal axis factor analysis in Study 2. Based on the responses of $N = 109$ participants. Simulated data depict the output of a parallel analysis with randomly generated eigenvalues (Horn, 1965).

respective factor (see Table 10). Based on our outlined criteria, we removed those items with factor loadings of .80 or below from further analyses.

Taken together, these results indicate excellent reliability and provide preliminary evidence for a two-factor structure for the selected exhaustion and recovery items. However, due to theoretical and statistical limitations, exploratory factor analysis cannot provide conclusive results regarding the construct validity of a scale (e.g., Costello & Osborne, 2005). Thus, in a next step we conducted confirmatory factor analysis to further test the two-factor structure of the items selected in Study 2.

Study 3

In the third study, we examined the construct validity of the two-factor structure using confirmatory factor analysis on a new data set unrelated to Study 2. Our a priori hypothesis was that a two-factor measurement model would fit the data better than a one-factor measurement model. We also expected a moderate to strong negative correlation between the latent exhaustion and recovery variables based on our findings in Study 2 and others' prior work (e.g., Demerouti et al., 2012).

Method

Participants. Participants filled out the exhaustion and recovery items immediately before and after an introductory Psychology lecture lasting 90 minutes. Initially, our inclusion criteria were that participants should fill out the questionnaires within 15 minutes after the lecture had begun (T1) and within 15 minutes after the lecture had ended (T2). However, of the 180 participants who met the 15-minute criteria for T1, only 65 also met the 15-minute criteria for T2. Thus, we did not include T2 in the confirmatory factor analyses and focused exclusively on T1. The final sample consisted of 180 Psychology students (72% female) aged between 18 and 37 years ($M = 21.83$, $SD = 3.46$).

Materials and procedure. Upon entering the lecture hall, students saw a link to the T1 online questionnaire projected on the front screen. The lecturer asked students if they were willing to fill out the questionnaire and made sure to mention that they should do so before the lecture started. The link led participants to a brief description of the study and the informed consent prompt. After consenting, participants indicated their age, gender, general life satisfaction and physical fitness. Then they were presented with the $n = 9$ exhaustion items and $n = 5$ recovery items selected in Study 2 (see Table 10). Items were worded and coded exactly as in Study 2. At the end of the lecture, the link to the T2 online questionnaire consisting of the same items was projected on the front screen, and the lecturer again asked the students if they were willing to fill out the questionnaire within the next minutes.

Statistical analysis. We conducted confirmatory factor analysis using the lavaan package (Rosseel, 2012) in R (R Core Team, 2018). To test our hypothesis, we compared the single factor model with a two correlated factors model. We determined the best-fitting model using the chi-square difference test, the Root Mean Square Error of Approximation (RMSEA) and its 90% confidence interval, the Standardized Root Mean Square Residual (SRMR), the Comparative Fit Index (CFI), as well as the Tucker-Lewis Index (TLI). Regarding the construct validity of the two-factor model, we adhered to the guidelines by Hu and Bentler (1999), who suggest that for continuous data, RMSEA should be close to .06 or below, SRMR should be close to .08 or below, and CFI as well as TFI should be close to .95 or above. Regarding reliability, we excluded items with poor communalities ($R^2 < .30$) from the measurement model. When an item was indexed to be excluded, we compared the model without the item against the model with the item using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and favored the model with lower values on these indices. Regarding post hoc model modification, we examined the standardized residuals and modification indices to detect potential sources of misfit. Standardized residuals exceeding the critical z-score of 2.58 and modification indices exceeding the critical chi-square difference of 3.84 were deemed significant. Finally, we deemed the measurement model to have acceptable convergent and divergent validity if the Average Variance Extracted (AVE) for the latent variables was higher than .50.

Results and Discussion

The data violated the assumption of multivariate normality (Mardia's test of multivariate kurtosis = 32.34, $p < .001$). Therefore, we used a robust maximum likelihood estimation with the Satorra-Bentler scaling correction to the chi-square test statistic (Satorra

& Bentler, 2001) in all confirmatory factor analyses. The results of the model comparisons are depicted in Table 11. In line with our hypothesis, the two-factor model with correlated latent variables fit the data better than the single-factor model, scaled $\Delta\chi^2(1) = 83.98$, $p < .001$. However, as can be seen in Table 11, the overall goodness-of-fit measures of the two-factor model indicate a poor fit to the data. Thus, in a next step we looked at the item communalities to decide if we should exclude any unreliable items. All items had communalities higher than .30, except for the exhaustion item "*Right now I feel nervous*", which had a value of .16. As the model without this item had lower AIC and BIC values compared to the model with the item included (see Table 11), we decided to exclude the item from further analyses. Nevertheless, the resulting model still did not have an acceptable fit to the data. To detect potential sources of misfit, we next looked at the standardized residuals and modification indices. The error covariance between the exhaustion items "*Right now I'm in a bad mood*" and "*Right now I feel sickened by everything*" had a significant standardized residual score ($z = 3.23$) and the largest modification indices value ($\Delta\chi^2(1) = 20.04$). We deemed a free estimation of this otherwise restricted parameter as warranted, because both items may share common sources of error variance due to their semantic similarity. The model with the error covariance fit the data better than the model without the error covariance, scaled $\Delta\chi^2(1) = 6.22$, $p < .05$. Including this error covariance in the model resulted in an acceptable overall model fit, RMSEA = .07, 90% CI [.047, .092], SRMR = .04, CFI = .96 and TLI = .95. The AVE was .53 for the latent recovery variable and .55 for the latent exhaustion variable, therefore we deemed this model to have acceptable convergent and divergent validity. The standardized factor loadings, item communalities, and factor correlation for this model are reported in Table 10. The complete model with the additional unstandardized factor loadings, factor (co)variances, and error (co)variances, is depicted in Figure 2.

Table 11

*Goodness-of-Fit Indicators of Nested and Non-Nested Models for Exhaustion and Recovery (*N *= 180).*

Model	χ^2	*df*	$\Delta\chi^2$	RMSEA [90% CI]	SRMR	CFI	TLI	AIC	BIC
				Hypothesis Test					
Single Factor	268.59***	77	–	.15 [.136, .170]	.62	.76	.72	7245.9	7380.0
Two Factors – Uncorrelated	234.70***	77	–	.12 [.102, .137]	.24	.85	.83	7120.3	7254.4
Two Factors – Correlated	155.94***	76	83.98***	.09 [.066, .105]	.05	.93	.91	7024.1	7161.4
				Model Modification					
Two Factors – Item Drop	124.47***	64	–	.08 [.060, .103]	.05	.94	.93	6437.0	6564.7
Two Factors – Error Cov	108.27***	63	6.22*	.07 [.047, .092]	.04	.96	.95	6413.7	6544.6

Note. Estimates are based on robust maximum likelihood estimation with the Satorra-Bentler scaling correction.

The Two Factors – Item Drop model excludes the nervousness exhaustion item based on its poor communality. The Two Factors – Error Cov model additionally allows for an error covariance between the “bad mood” and “sickened by everything” exhaustion items.

*** $p < .001$. * $p < .05$

The results of this study provide further evidence for a correlated two-factor structure for the exhaustion and recovery items. Based on the results reported in this study, we finalized the Exhaustion and Recovery Scale with n = 8 exhaustion items and n = 5 recovery items (see Appendix B).

Study 4

In Study 4, we assessed participants' exhaustion and recovery ratings immediately before and after a period of effortful cognitive activity, along with their ratings on momentary mood, wakefulness, and calmness. Doing so allowed us to test whether the scale could detect changes in psychological functioning resulting from cognitive effort, as well as the degree to which the scale corresponds to conceptually similar constructs (i.e., concurrent validity).

We expected that persons report higher levels of exhaustion and lower levels of recovery after compared to before the period of effortful cognitive activity. Based on the mood regulation perspective of recovery (e.g., Sonnentag & Fritz, 2007), we also expected a positive (negative) relationship between recovery (exhaustion) and mood. Furthermore, given that sleepiness and exhaustion are typically confounded (e.g., Balkin & Wesensten, 2011), we also expected the same pattern for wakefulness. Finally, we did not expect a strong relationship between recovery and exhaustion with calmness, since one can also feel recovered and tense (tense energy) or exhausted and calm (calm tiredness; Thayer, 1989).

Method

Participants. One hundred and two persons aged between 19 and 74 years (M = 27.27, SD = 10.85; 46% female) participated in this study.

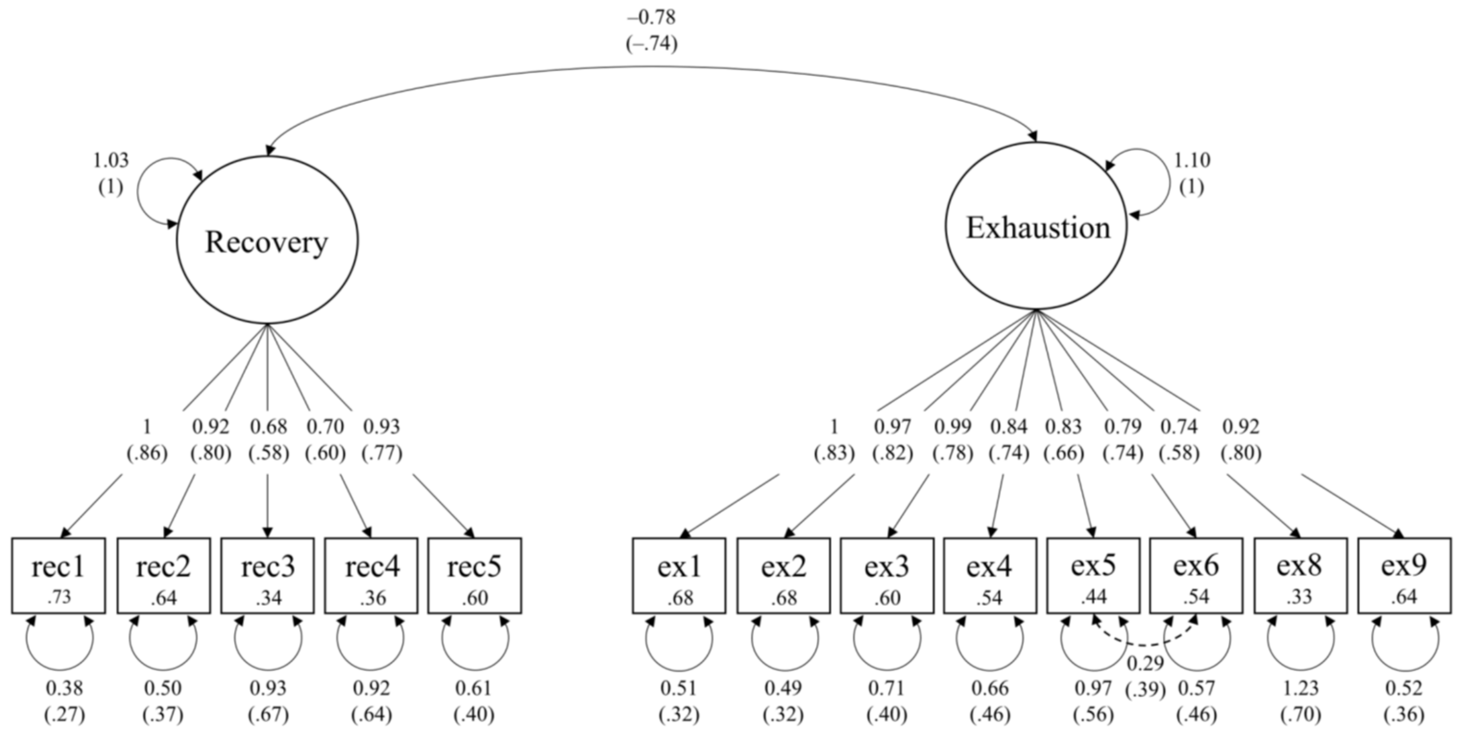

Figure 8. Path diagram of the correlated two-factor measurement model without the "I feel nervous" item (ex7) and with a freely estimated error covariance between the "I'm in a bad mood" (ex5) and "I'm sickened by everything" (ex6) items in Study 3. Based on the responses of $N = 180$ participants. The standardized parameter estimates are reported in brackets. All parameter estimates are statistically significant at $p < .001$. The item communalities are listed below the item descriptions. Full item descriptions are reported in Table 10. Goodness-of-fit indices for this model are reported in Table 11.

Materials and procedure. This study was part of a larger experiment measuring the relationship between subjective time perception and exhaustion. Participants completed a series of effortful cognitive tasks (Kreuzpointner, Lukesch, & Horn, 2013)[2]. Immediately before and after the tasks, participants filled out the finalized Exhaustion and Recovery scale that was worded exactly as in Studies 2 and 3. In addition, they filled out the Multidimensional Mood State Questionnaire (Steyer et al., 1997). This questionnaire assesses psychological functioning on three bipolar dimensions: Good mood (vs. bad mood), wakefulness (vs. tiredness), and calmness (vs. nervousness). Each dimension was measured with four items on a scale of 0 (*not at all*) to 5 (*very much*). An example item is "*Right now I feel happy*" for good mood, "*Right now I feel rested*" for wakefulness, and "*Right now I feel at ease*" for calmness.

Statistical analysis. We assessed the pre-post difference in scale means using a dependent samples *t* test. To examine the degree of association between the scales and the related constructs, we computed the Pearson product-moment correlation coefficients for the two scale means of the Exhaustion and Recovery Scale and the three dimensions of the Multidimensional Mood State Questionnaire.

[2] The experiment included two conditions: The "time flies" condition ($n = 41$) was told that the tasks would last 70 minutes, and the "time drags" condition ($n = 61$) was told that the tasks would last 50 minutes. In actuality, the tasks always lasted exactly 60 minutes for both conditions. As a manipulation check, participants were then asked to indicate how slowly or fast time had passed for them during these tasks on a scale of 0 (*rather slowly*) to 6 (*rather quickly*). As both conditions did not differ regarding this rating with $t(97.88) = 1.07$, $p = .29$, we concluded that the manipulation had not been successful and thus collapsed both conditions into one sample for the subsequent analyses.

Results and Discussion

The Exhaustion and Recovery Scale was sensitive to detecting changes in psychological functioning brought about by working on a series of cognitive tasks for one hour. People felt more exhausted after (M = 1.44, SD = 1.10) compared to before (M = 1.11, SD = 0.88) the tasks, $t(101)$ = -3.23, 95% CI of the mean difference [-0.53, -0.13], d = -0.23. Conversely, people felt less recovered after (M = 2.03, SD = 0.94) compared to before (M = 2.38, SD = 0.86) the tasks, $t(101)$ = 4.05, 95% CI of the mean difference [0.18, 0.51], d = 0.29. Due to insufficient sample size, we were not able to test for measurement invariance across the two time points, so these results need to be interpreted with caution.

The Pearson product-moment correlations are depicted in Table 12. As expected, the recovery subscale was positively associated with both good mood and wakefulness, while exhaustion was negatively associated with good mood and wakefulness, before and after the cognitive tasks. There were no substantial associations between recovery and exhaustion with calmness, except for a small negative correlation between exhaustion and calmness before the tasks.

General Discussion

The aim of this research was to combine various heterogeneous self-report measures of exhaustion and recovery into a single, general exhaustion and recovery scale. A series of four studies revealed excellent reliability of the selected items, a robust two-factor structure with generally high item factor loadings and communalities, as well as first evidence for concurrent validity.

Table 12

Pearson Product-Moment Correlation Coefficients of the Exhaustion and Recovery Scale Means and the Multidimensional Mood State Questionnaire Subscales (Study 4).

Scale mean	1	2	3	4	5
1. Recovery	–	-.45***	.42***	.58***	.02
2. Exhaustion	-.48***	–	-.66***	-.70***	-.05
3. Mood	.49***	-.72***	–	.57***	-.15
4. Wakefulness	.58***	-.53***	.55***	–	.11
5. Calmness	.08	-.23*	.08	.33***	–

Note. Correlations below the main diagonal were obtained before the cognitive tasks, correlations above the main diagonal were obtained after the cognitive tasks.

*** $p < .001$. * $p < .05$

Applicability of the Exhaustion and Recovery Scale

The generality of the Exhaustion and Recovery Scale allows for its implementation in various everyday life situations. For example, the scale's brevity could prove advantageous for assessing multiple measurement occasions throughout a day. This enables researchers to examine daily fluctuations of exhaustion and recovery levels in various life domains, such as in the work or leisure context. In addition, the scale takes into account the multidimensionality of the constructs and enables a more refined and complete assessment of exhaustion and recovery compared to previous measures.

Limitations and Future Research

The presented studies have some limitations worth noting. First, we did not assess measures of scale reliability other than internal consistency. As Henson (2001) notes, "internal consistency coefficients are not direct measures of reliability, but rather are theoretical estimates derived from classical test theory" (p. 177). Hence, future studies should establish more direct measures of scale reliability (e.g., test-retest reliability) to address open questions such as the stability of individual scores over time.

Second, researchers interested in measuring exhaustion and recovery within-persons over multiple time points should first establish the scale's longitudinal measurement invariance. Similarly, researchers interested in assessing age-related differences in exhaustion and recovery should also first establish the scale's measurement invariance across these different age groups.

Conclusion

Overall, the Exhaustion and Recovery Scale is a psychometrically sound, easily administered, and brief self-report measure of momentary feelings of exhaustion and recovery. The novel contribution is that it combines items from several existing self-report measures into a single, general scale of exhaustion and recovery. Whereas prior questionnaires have mainly viewed exhaustion and recovery as opposite ends of a bipolar construct, the Exhaustion and Recovery Scale assesses both constructs separately – an important step forward considering recent findings of moderate to strong, but not perfect correlations between exhaustion and recovery.

OVERALL DISCUSSION

The overarching aim of this thesis was to (1) examine the role of mood, perceived opportunity costs, and subjective time perception as psychological indicators of exhaustion and recovery, and (2) investigate age-related differences in exhaustion, recovery, and their proposed indicators. In this section, I provide a brief overall summary of the main results and evaluate their implications for the proposed motivational account of exhaustion and recovery. I then discuss the necessity to consider physical and mental aspects of exhaustion and recovery separately. Afterwards, I shed more light on the cost-benefit mechanism that is thought to underlie the phenomenology of exhaustion and recovery by (1) reviewing the role of effort, interest, and boredom as select inputs that might be particularly relevant in the context of exhaustion and recovery, and (2) discussing the role of goal focus for shaping the value of effort. Thereafter, I outline possible boundary conditions of the proposed account, address general methodological limitations of the current studies, and make suggestions for future research. Finally, I provide some practical implications of the present work before ending with the final conclusions.

Summary of the Main Findings

Part I introduced a comprehensive motivational account of exhaustion and recovery addressing the question of how people determine when an activity has helped them to recover or when it has exhausted them. We hypothesized that changes in mood, perceived opportunity costs, and subjective time perception during an ongoing effortful or relaxing activity provide valuable information about one's current state of exhaustion and recovery. Specifically, we maintained that as long as an activity's cost-benefit ratio is favorable (i.e., the activity nets more benefits than costs), a person experiences positive mood, negligible opportunity costs, and an accelerated sense of the pace of time. In this motivational state, the person perceives the activity as contributing to her ongoing recovery (relaxing activity) or not yet exhausting (effortful activity). The behavioral response is continued activity engagement. We further maintained that if an activity's cost-benefit ratio turns unfavorable (i.e., nets more costs than benefits), a person experiences a gradual decrease in positive mood, an increase in perceived opportunity costs, and an extension of the felt pace of time. In this motivational state, the person perceives the activity as not contributing to her recovery anymore (relaxing activity) or as increasingly exhausting (effortful activity). The behavioral response is disengagement from the activity. Furthermore, taking a life-span developmental perspective, we derived two different age hypotheses: Older adults, as compared to younger adults, might feel exhausted and recovered faster, because they more readily detect increases in opportunity costs during an ongoing effortful or relaxing activity. Alternatively, older adults might feel exhausted more slowly and feel recovered faster, because they perceive time as passing more quickly during an effortful or relaxing activity compared to younger adults.

Part II sought to empirically examine one part of the proposed account. Specifically, Part II focused on the role of mood, opportunity costs, and subjective time perception as indicators of recovery from exhaustion. Study 1 explored people's lay beliefs about what thoughts, feelings, and behaviors indicate to them exhaustion and recovery. The central finding of Study 1 is that people think of changes in mood, but not of changes in perceived opportunity costs or in subjective time perception, as a salient indicator of exhaustion and recovery. Study 2 experimentally induced a state of exhaustion by means of a 20-minute high intensity interval training and examined the time courses of recovery, mood, perceived opportunity costs, and subjective time perception during a subsequent 20-minute relaxation video, as well as the correlated within-person change between these variables (i.e., the extent to which these variables "travel together" over time). The central finding of Study 2 is that within-person variability in mood, but not in perceived opportunity costs or in subjective time perception, was related to within-person variability in recovery – despite a pronounced average increase in opportunity costs and a pronounced extension of the pace of time during the relaxation video. Studies 3 and 4 aimed to replicate the findings of Study 2 and additionally tested the hypothesis that perceived opportunity costs are causally related to recovery from exhaustion by experimentally inducing high or low opportunity costs between the exhaustion and recovery period and testing the impact of this between-person manipulation on the subjective speed of recovery. Despite a successful manipulation of opportunity costs in Study 4, perceiving high vs. low opportunity costs during the recovery period did not have an impact on recovery.

Part III focused on age-related differences in the subjective availability of energy for goal pursuit as well as in short-term exhaustion, recovery, and their proposed indicators. Study 1 examined age-related differences in (1) people's lay beliefs about energy, (2) the perceived amount of energy available for activities related to different functional domains (i.e., physical, mental, social, emotional), and (3) within- and cross-domain energy spillover. With increasing age, people were more likely to endorse a non-limited belief of energy, were more likely to report to have less energy available for physical activities in general (but not for personally relevant physical activities), and were more likely to report cross-domain energy spillover after engaging in demanding physical activities, such that they reported to have less energy available for subsequent social and emotional activities. Aiming to better understand these results, Study 2 harkened back to the laboratory study design employed in Part II, Studies 2-4, and examined age-related differences in the role of mood, perceived opportunity costs, and subjective time perception as indicators for both exhaustion and recovery. The central finding of Study 2 is that older adults reported a steeper initial increase in exhaustion and opportunity costs during a 20-minute high intensity interval training, but converged again with the younger age groups at the close of the exercise.

Part IV examined the role of mood, perceived opportunity costs, and subjective time perception as indicators of recovery at a different time scale: the day level. Focusing on university students' summer break after a demanding exam period, Part IV employed a daily diary design and assessed students' retrospective judgments about their daily recovery, mood, opportunity costs, and subjective time perception, controlling for relevant covariates of daily recovery over 21 consecutive days. The central finding of Part IV is that within-person variability in daily mood and opportunity costs was related to variability in recovery, such that on days on which students reported higher-than-usual mood and lower-than-usual opportunity costs, they also reported higher-than-usual recovery, over and above daily psychological detachment, relaxation, mastery, and control (Sonnentag & Fritz, 2007).

Part V was concerned with the development and initial validation of a domain-general exhaustion and recovery scale that can be assessed both as a trait and state measure. Study 1 generated a pool of items from existing exhaustion and recovery questionnaires. Study 2 tested the reliability and the factorial structure of the selected items using exploratory factor analysis. Study 3 cross-validated the factorial structure on an independent data set using confirmatory factor analysis. Study 4 established the sensitivity of the scale in detecting short-term fluctuations in exhaustion and recovery, and assessed its concurrent and divergent validity. The resulting scale was included in all the studies reported in Parts II-IV as a trait measure of exhaustion and recovery (except for Study 1 in Part II). Notably, Study 4 also included a between-person manipulation of retrospective time perception following a demanding 90-minute cognitive task. However, the manipulation check indicated that the manipulation had not been successful in altering participants' retrospective judgments about the felt pace of time during the task. Accordingly, the manipulation did not influence perceived exhaustion and recovery after compared to before the demanding task.

Psychological Indicators of Exhaustion and Recovery: Weighing the Evidence

What does the accumulated empirical evidence in Parts II-V tell us about the proposed role of mood, perceived opportunity costs, and subjective time perception as psychological indicators of recovery and exhaustion outlined in Part I? In the following, I relate the central findings of this thesis to the proposed motivational account of exhaustion and recovery.

Mood

Across all studies and different time scales, we consistently found support for the hypothesized positive relationship between mood and recovery: Being in a positive mood (e.g., "feeling good") was the most frequently mentioned indicator of recovery (Part II, Study 1). At the activity level, interindividual differences in intraindividual variability in mood were positively related to variability in recovery, such that people who reported a steeper increase in mood during a relaxing activity (i.e., watching an aquatic documentary or listening to a mindfulness-based relaxation video) also reported a steeper initial increase in recovery (Part II, Studies 2-4 and Part III, Study 2). At the day level, students reported higher recovery on days on which they were in a better-than-usual mood during their summer break, over and above other covariates of daily recovery (Part IV). Finally, at the dispositional level, people who generally report higher levels of positive mood also tend to report feeling more recovered and less exhausted in their daily lives (Part II, Studies 2-4, Part III, Part IV, and Part V, Study 4).

We also found support for the hypothesized negative relationship between mood and exhaustion: Being in a negative mood (e.g., "feeling bad") was the fifth highest mentioned indicator of exhaustion (Part II, Study 1). At the activity level, interindividual differences in intraindividual variability in mood were negatively associated with variability in exhaustion, such that people who reported a steeper decrease in mood during a 20-minute high-intensity interval training also tended to report a steeper increase in exhaustion (Part III, Study 2).

Lastly, people who generally report higher levels of negative mood also tend to report feeling more exhausted and less recovered in their daily lives (Part II, Studies 2-4, Part III, Part IV, Part V, Study 4).

Taken together, then, people mostly endorse the belief that being in a good mood (bad mood) provides valuable information about their current state of recovery (exhaustion). This pattern is also mirrored in people's actual experiences during an ongoing effortful and relaxing activity, such that changes in mood are related to changes in recovery and exhaustion. These findings are in line with previous work stressing the importance of mood regulation for recovery (Larsen, 2000; Parkinson & Totterdell, 1999; Sonnentag & Fritz, 2007; Thayer et al., 1994). However, whereas prior research has provided evidence for the temporally delayed relationship between mood and recovery (e.g., Oerlemans et al., 2014; Sonnentag et al., 2008; Sonnentag & Zijlstra, 2006) and has assessed this relationship mainly at the between-person level (Sonnentag et al., 2017), this thesis provides compelling evidence for the *concurrent within-person* associations between mood, recovery, and exhaustion.

However, correlation does not imply causation. With the current empirical evidence, we cannot draw firm conclusions about the *direction* of these relationships. For instance, does mood inform one's recovery progress, or does the extent of recovery influence one's current mood? Despite our strong theoretical position that people take the valence of their mood as information about the goodness or badness of their current environment (Clore et al., 2001; Clore & Huntsinger, 2007; Huntsinger et al., 2014; Schwarz, 2011; Schwarz & Clore, 2003) and that the valence of people's mood is implicated in their decisions to stay engaged or disengage from a goal (Martin, 2001; Martin et al., 1993), the current studies cannot provide a strong test of these directed hypotheses. Thus, absent a mood manipulation, as of yet we cannot draw a decisive conclusion regarding the causality of the mood-recovery and mood-exhaustion relationship (but see the problems involved with manipulating mood in the present studies discussed in Part II).

Furthermore, the present studies cannot provide a strong test of the hypothesis that positive mood begins to gradually decline once people have sufficiently recovered (i.e., attained their goal of recovery), as a motivational cue for goal disengagement (Part I). A strong test of this dynamic hypothesis would necessitate a behavioral measure of goal disengagement (e.g., participants press a button once they feel sufficiently recovered *and* want to do something else) to pinpoint the exact point in time when the net benefits of disengaging surpass the net benefits of staying engaged in the relaxing activity, rather than relying on indirect information about goal attainment through participants' subjective recovery time courses. For instance, a person might feel that the relaxing activity has sufficiently contributed to her recovery but might nevertheless be motivated to stay engaged in the activity past the point of recovery because of an inherent interest in, or enjoyment of, the activity itself (Csikszentmihalyi, 1975). Therefore, while the current studies have established a positive association between mood and *ongoing* recovery, they cannot speak to the hypothesized negative association between mood and recovery after goal attainment.

Perceived Opportunity Costs

Overall, the accumulated empirical evidence does not provide support for the hypothesis that perceived opportunity costs are related to recovery. First, people do not perceive thinking about or wanting to engage in attractive alternatives as a salient indicator of recovery (Part II, Study 1). Second, despite a steep average increase of opportunity costs during a relaxing activity, interindividual differences in intraindividual variability in opportunity costs were not associated with variability in recovery (Part II, Studies 2-4 and Part III, Study 2). Third, and perhaps most telling, experimentally manipulating opportunity costs (i.e., thinking about an attractive vs. an unattractive alternative activity) before a relaxing activity and keeping these costs salient during the activity was unrelated to the subjective speed of recovery (Part II, Study 4). Only at the day level did we find the expected relationship between opportunity costs and recovery: Students reported higher recovery on days when they perceived lower-than-usual opportunity costs (operationalized as the extent to which one would have wanted to experience a closing day differently), over and above other covariates of daily recovery (Part IV).

In comparison, the empirical evidence for the hypothesis that opportunity costs are related to exhaustion is more favorable: Although small in effect size (*d*s between 0.14 and 0.20), perceived opportunity costs were consistently higher on average immediately after compared to before effortful physical activity (Part II, Studies 2-4). Perceived opportunity costs also markedly increased *during* physical exercise on average (Part III, Study 2). Furthermore, interindividual differences in intraindividual variability in opportunity costs were positively related to variability in exhaustion during physical exercise, such that persons who reported a steeper increase in opportunity costs also tended to report a steeper increase in exhaustion (Part III, Study 2).

Taken together, then, perceiving an increase in opportunity costs during a relaxing activity does not provide information about one's recovery progress. In contrast, perceiving an increase in opportunity costs during an effortful activity is associated with feelings of exhaustion. Furthermore, experiencing less day-level opportunity costs is related to feeling more recovered on that day. However, it remains unclear to what extent activity-level opportunity costs are comparable to day-level opportunity costs, because prior research (e.g., Hockey, 2013; Hofmann et al., 2019; Kurzban, 2016; Kurzban et al., 2013) has exclusively focused on the former. To the author's knowledge, this thesis provides the first attempt at operationalizing day-level opportunity costs. As such, the construct of day-level opportunity costs necessitates further theoretical and empirical validation before drawing any firm conclusions about its impact on recovery. It is interesting to note, however, that day-level opportunity costs explained variation in daily recovery over and above feelings of control (i.e., feeling that one can decide for oneself what to do on a given day), suggesting that wanting to experience a closing day differently is a qualitatively different experience than the mere feeling of being in control that day.

Similar to mood, the direction of the relationship between activity-level opportunity costs and exhaustion remains elusive. Although prior theoretical work has positioned opportunity costs as an antecedent of exhaustion, such that opportunity costs lead to exhaustion through an increase in perceived effort (e.g., Hockey, 2013; Hofmann et al., 2019; Kurzban, 2016; Kurzban et al., 2013), as of yet there exists no empirical evidence for this proposition. For instance, Hofmann et al. (2019) have shown that experiencing opportunity costs leads to an increase in the sense of effort and a devaluation of the current activity, but their work has not examined the direct influence of opportunity costs on subjective exhaustion. In the present work, we sought to experimentally manipulate opportunity costs before a recovery period, but not before an exhaustion period. Therefore, one way to test for causality in the present study design would be to administer the opportunity costs manipulation from Part II, Study 4 immediately before the exhaustion period, and to keep these induced opportunity costs salient throughout. According to the proposed theoretical account (Part I), people should feel exhausted faster if they perceive high compared to low opportunity costs, provided that opportunity costs are indeed taken as an indicator of exhaustion.

Subjective Time Perception

Across studies, we found no strong support for the hypothesis that the felt pace of time is related to recovery. First, people do not perceive a subjective acceleration of time as a salient indicator of recovery (Part II, Study 1). Second, despite a marked average extension of subjective time perception during a relaxing activity, interindividual differences in intraindividual variability in subjective time perception were not associated with variability in recovery (Part II, Studies 2-4 and Part III, Study 2). The one exception occurred at the day level: Students reported higher recovery on days that they felt had passed faster than usual (Part IV). However, this positive within-person association did not remain significant after controlling for other covariates of daily recovery.

The varying contribution of subjective time perception to recovery across different time scales may – at least in part – be explained by the differential mechanisms underlying *prospective* and *retrospective* time perception. In particular, the repeated micro-assessments of subjective time perception during a relaxing activity in Part II, Studies 2-4 and Part III, Study 2 might have progressively directed participant's attention away from their external environment and toward their "inner clock," thereby resulting in the aversive feeling that "time drags" (Zakay & Block, 1997). In such a state, people are more likely to feel bored (Bench & Lench, 2013; Westgate & Wilson, 2018; Zakay, 2014). Indeed, we found medium to large within-person associations between subjective time perception and boredom, such that people who reported a steeper extension of the pace of time during the recovery period also tended to report a steeper increase in boredom (Part II, Study 4 and Part III, Study 2). In comparison, people's daily retrospective judgments about how quickly or slowly their day has passed (Part IV) might have been mainly based on the number of recalled events during the day. According to the contextual change model (Block & Reed, 1978), the *less* contextual changes (i.e., events) are recalled during a specific time period, the *faster* that time period seems to have passed in retrospect. This is because encountering only few changes during a day results in a less rich memory trace that, in turn, decreases the remembered duration of the day. Perhaps, then, the positive association between daily time perception and recovery can be explained by this account: When people recalled less contextual changes or events throughout a specific day, they might have deemed that day less busy and stressful, and might therefore have concluded that this day was helping them to recover.

With regard to exhaustion, people do not perceive a subjective extension of the pace of time as a salient indicator of exhaustion (Part II, Study 1). However, interindividual differences in intraindividual variability in subjective time perception were negatively related with variability in exhaustion, such that people with a steeper extension of the pace of time also tended to report a steeper increase in exhaustion during physical exercise (Part III, Study 2). An attempt at manipulating subjective time perception during an effortful mental activity with a retrospective time perception paradigm did not prove successful (Part V, Study 4); therefore, as of yet no strong conclusions can be drawn about the causality of this relationship. Note, however, that in a recent study employing a similar retrospective time perception paradigm, Dillard et al. (2019) found that people who had been led to believe that time had passed faster than expected during a 30-minute vigilance task did *not* report different levels of task enjoyment, perceived workload, and stress as compared to those people who had been led to believe that time had passed slower than expected (cf. Gable & Poole, 2012; Sackett et al., 2010). This finding calls into question the causal influence of retrospective time perception on subjective exhaustion. It is still open, however, if the felt extension of time *during* an effortful activity causally relates to subjective exhaustion.

Age-Related Differences in Exhaustion and Recovery

Part I introduced two age hypotheses that were partially tested in Part III, Study 2: (i) Older adults more readily detect opportunity costs during an ongoing exhausting or recovery activity, and therefore feel exhausted and recovered faster compared to younger adults, and (ii) older adults perceive time as passing more quickly during an ongoing exhausting or recovery activity, and therefore feel exhausted more slowly or recovered faster compared to younger adults. With respect to the first hypothesis, older adults reported a steeper *initial* increase in perceived opportunity costs and subjective exhaustion during an exhausting activity (i.e., 20-minute high-intensity interval training). However, the older and younger age groups converged again in their levels of opportunity costs and exhaustion at the close of the exercise (see Part III for a discussion on potential theoretical and methodological explanations for these results). There were no age-related differences in the level and rate of change in perceived opportunity costs or subjective recovery in a subsequent recovery activity (i.e., listening to a 20-minute mindfulness-based relaxation video).

Why were there no age-related differences in the initial level of subjective recovery after exhaustion? One reason for this initial similarity might be that older adults, as compared to younger adults, generally perceive to have *similar* levels of energy available for activities after having exerted themselves physically (except for social and emotional activities, for which older adults report to have less energy available; Part III, Study 1). This finding is also in line with the *overpowering hypothesis*, which states that age-related differences in affective responding are particularly pronounced in unpleasant environments that are *complex* (i.e., highly resource-demanding situations that older adults cannot properly handle at their current level of functioning; Wrzus, Müller, Wagner, Lindenberger, & Riediger, 2013; see also Labouvie-Vief, Gilet, & Mella, 2014). The physical exercise employed in Part III, Study 2 might not have constituted a sufficiently complex environment; therefore, the sampled older adults might not have perceived an overtaxing of their capacities (see also the possibility of selection bias discussed in Part III). Furthermore, the similar rate of change in subjective recovery between the age groups is in line with research showing that the self-reported time needed to recover from high-arousing negative affect following a stressful situation does not change with age (Wrzus, Müller, Wagner, Lindenberger, & Riediger, 2014). Taken together, it seems that the extent and rate of subjective recovery does not differ with age (but see Wrzus et al., 2014, for potential age-related differences in *physiological* reactivity and recovery).

Alternatively, the fact that the average initial increase in recovery (i.e., the linear change from the first to the second measurement occasion) during the recovery period was much more pronounced in Part III, Study 2 (b = 2.15) as compared to the prior studies (bs between 0.67 and 1.06 in Part II, Studies 2-4) might be an indication that we were unsuccessful at targeting the sensitive time period during which these age-related differences might have occurred (Bolger & Laurenceau, 2013). In particular, the 2-minute time interval between the first and second measurement occasion might have been too large to capture any meaningful age-related differences in the within-person change in recovery, as it seems that a substantial amount of the recovery progress unfolded during these first two minutes of the 20-minute mindfulness-based relaxation video.

With regard to the second hypothesis, Part III, Study 2 further revealed a small cross-level main effect of age on the felt pace of time during both the exhaustion and recovery period, such that older adults overall tended to perceive time as passing more quickly compared to younger adults. To better understand this result, a follow-up analysis (not reported in Part III and thus elaborated in more detail here) directly comparing the age groups of younger and older adults (coded: 0 = younger adults, 1 = older adults) revealed a non-significant main effect of age on time perception for the exhaustion period (b = 0.53, 95% CI [-0.09, 1.15]) and a significant main effect for the recovery period (b = 0.87, 95% CI [0.14, 1.62]). However, this effect did not remain significant when all measurement occasions were combined to increase power (N = 2940 observations; b = 0.59, 95% CI [-0.02, 1.19]). Therefore, overall, the current data does not provide strong support for the hypothesis that older adults perceive time as passing more quickly during an effortful or relaxing activity as compared to younger adults.

This null finding seemingly contradicts the well-known adage that “time seems to speed up as we get older.” However, the current data is consistent with past research that has also found no differences in the felt pace of time during everyday life activities between younger and older adults using experience sampling methodology (Droit-Volet & Wearden, 2015, 2016). Nevertheless, the relationship between subjective time perception and aging might be more nuanced: John and Lang (2015) found that the *type* of activity moderates the relationship between subjective time perception and age, and that this moderation can partly be explained by a limited future time perspective. In particular, the authors found that older adults reported an acceleration of the subjective progression of time during everyday life activities that were categorized as *productive* (i.e., activities that serve a longer-term outcome, such as paid work or social engagement), but no association between time perception and age for activities that were categorized as *regenerative-consumptive* (i.e., activities that serve immediate need satisfaction, such as resting, eating, or self-care; Klumb & Baltes, 1999). John and Lang (2015, p. 1836) conclude that “the experience that time passes quickly when trying to attain long-term goals in everyday life reflects older adults’ awareness of lifetime constraints on goal attainment in daily life.” Hence, older adults might only perceive a subjective acceleration of the passage of time in contexts where they are confronted with their limited remaining time in life – an assumption that is unlikely to have been met while listening to a 20-minute mindfulness-based relaxation video.

On the Divergence of Physical and Mental Exhaustion and Recovery

As we set out to conceptualize our account in Part I and ran the first two exercise studies in Part II, we did not deem it necessary to make a distinction between physical and mental aspects of exhaustion and recovery, believing them to be “two sides of the same coin” (Evans et al., 2016; Müller & Apps, 2019; but see Inzlicht & Marcora, 2016). However, as became clear in Part II, Study 4 and Part III, Study 2, the distinction between physical and mental recovery and exhaustion proved necessary indeed: In these studies, within-person changes in both functional domains were only weakly to moderately positively correlated (*r*s between .25 and .48) and, more importantly, showed differential between-person time courses during the exhaustion and recovery periods. Next, I provide some potential explanations for this divergent pattern of results.

First, the inverted U-shape of the average mental recovery time course during physical exercise (Part III, Study 2) is in line with more recent neurocognitive perspectives on the acute exercise–cognition interaction: Schmit and Brisswalter (2018) propose that the efficiency of executive functioning during prolonged physical activity is *dynamic*, such that its efficiency first increases and later decreases. Briefly, at the beginning of exercise, physiological arousal increases rapidly, which in turn up-regulates prefrontal cortex activity (e.g., through an increase in the release of noradrenaline and dopamine in the prefrontal cortex), resulting in enhanced executive functioning and self-regulation (Ramos & Arnsten, 2007). In these early stages of the workout, participants might thus have perceived an increase in mental recovery. However, as time-on-task progresses, physiological constraints due to exercising (e.g., muscle soreness and pain, impaired respiration) become more salient. As a consequence, executive functioning is increasingly allocated towards regulating this afferent feedback (e.g., by inhibiting muscle pain, monitoring bodily sensations, and regulating respiration; Meeusen et al., 2016). At some point in time, the exercise-induced arousal effect becomes insufficient to counteract the increasing regulatory demands put on the prefrontal cortex information processing system. In these later stages of the workout, participants might thus have perceived a decrease in mental recovery.

Second, with respect to the recovery period, compared to the steep initial average increase in *physical* recovery, there was a less pronounced initial average increase in *mental* recovery (b = 2.15 and b = 0.69, respectively; Part III, Study 2), or even no average change in mental recovery at all (*b* = -0.02; Part II, Study 4). These findings are in line with people's beliefs about cross-domain energy spillover: After a demanding physical activity, people generally do not perceive to have substantially less energy available for mental activities (Part III, Study 1). Therefore, people should not feel a strong need to recover in the mental domain when recovering from physical exercise. This line of reasoning is further supported by the effort-recovery model (Meijman & Mulder, 1998), which states that recovery in one functional domain (e.g., physical domain) is best achieved by ceasing all effortful activity in that domain, but does not preclude spending effort in another functional domain (e.g., mental domain). In fact, a series of studies has shown that acute physical exercise can even enhance subsequent mental performance (Chang, Labban, Gapin, & Etnier, 2012; Hogan, Mata, & Carstensen, 2013; Ludyga, Gerber, Brand, Holsboer-Trachsler, & Pühse, 2016; McSween et al., 2019; Roig, Norbrandt, Geertsen, & Nielsen, 2013). Conversely, and contrary to the predictions of the effort-recovery model, mental exertion can have a detrimental effect on endurance performance in subsequent physical exercise – a relationship that is in part mediated by an increase in the sense of effort during the physical exercise due to prior mental exertion (van Cutsem et al., 2017; but see McMorris, Barwood, Hale, Dicks, & Corbett, 2018). Alas, to date the relationship between physical and mental exhaustion and recovery remains poorly understood and is in dire need of further theoretical and empirical inspection.

Elucidating Potential Inputs to the Cost-Benefit Mechanism

The motivational account proposed in the present thesis assumes the (predominantly) unconscious weighing of subjective costs and benefits as the central mechanism underlying the phenomenology of exhaustion and recovery (for a detailed discussion on this, see Part I). The numerous costs and benefits associated with everyday life activities are without a doubt highly idiosyncratic, time-sensitive, and context-dependent. Nevertheless, it is necessary to provide some deliberations as to the kinds of costs and benefits that might be particularly relevant in the context of exhaustion and recovery, and how they relate to the proposed account in Part I. Arguably, the ultimate price of engaging in any activity is the time forgone on the next-best alternative – a direct consequence resulting from the fact that a person's executive functions can only be allocated toward a limited amount of activities at any given point in time (Kurzban et al., 2013; but see Dunn, Inzlicht, & Risko, 2017). Indeed, in the hectic rush of modern life, this time cost is likely to weigh particularly heavy on the dynamics of daily multiple goal pursuit. This section introduces three similarly ubiquitous subjective experiences (i.e., effort, interest, and boredom) as further contenders for psychological inputs to the cost-benefit mechanism.

Effort

To date, the phenomenology of effort has predominantly been conceptualized as aversive (Dreisbach & Fischer, 2012; Kurzban, 2016; Shenhav et al., 2017; Westbrook & Braver, 2015) and inherently costly (Kool & Botvinick, 2013, 2018; Kurzban et al., 2013; Navon & Gopher, 1979). This traditional view of effort is perhaps best illustrated in the long-held notion of humans as "cognitive misers" who, when given the choice between two otherwise equivalent tasks, prefer to choose the less demanding one (Allport, 1954; Hull, 1943; Kool, McGuire, Rosen, & Botvinick, 2010; for a study on physical effort, see Hartmann, Hager, Tobler, & Kaiser, 2013). Nevertheless, people clearly vary in their dispositional motivation to engage in effortful activities (Cacioppo & Petty, 1982; Cacioppo, Petty, Feinstein, & Jarvis, 1996) and in the extent to which they devalue effort (Westbrook, Kester, & Braver, 2013). Indeed, as with emotional experience more broadly (Barrett, 2013), recent work has demonstrated that "feelings arising during controlled performance are both heterogeneous and related to the objective efficacy of goal-directed actions" (Saunders, Milyavskaya, & Inzlicht, 2015, p. 1213), calling for a more nuanced and fine-grained perspective on subjective effort. Inzlicht et al. (2018) have coined the term "effort paradox" to illustrate that the experience associated with spending effort can vary from costly to valued, mainly depending on two factors. First, according to the effort heuristic, the outcome associated with an activity can become more valuable the more effort one invests for achieving it (Kruger, Wirtz, Van Boven, & Altermatt, 2004; Loewenstein, 1999; Norton, Mochon, & Ariely, 2012; Olivola & Shafir, 2013). Second, through the process of learned industriousness (Eisenberger, 1992) or the experience of flow (Csikszentmihalyi, 1975), the very notion of spending effort on a demanding activity can become valuable in its own right (see also Deci, 1975; Kruglanski et al., 2018). Thus, exerting effort can sometimes add value through increasing the probability of achieving attractive *external rewards*, through facilitating *intrinsic incentives*, or through enhancing the activity's perceived *instrumentality* for goal attainment and thus making it more desirable (Labroo & Kim, 2009).

How, then, is effort registered in the subjective cost-benefit ratio that is proposed to underlie the phenomenology of exhaustion and recovery? I maintain that perceiving an activity as effortful will not always be registered as a cost and, consequently, does not inevitably lead to exhaustion (cf. Müller & Apps, 2019). Rather, effort may sometimes be registered as a *benefit*, depending, for instance, on a person's dispositional motivation to seek out effort (Cacioppo et al., 1996) or the perceived rate of progress toward the desired outcome (Carver & Scheier, 2004). In fact, the proposed account of exhaustion and recovery in Part I provides a novel explanation as to why the sense of effort is sometimes perceived as aversive and other times as pleasant: When exerting effort on a task is inherently valuable to a person or is expected to lead to valued outcomes, then effort is registered as a benefit in the cost-benefit ratio of said task, thus contributing to a pleasant state and shielding the person from the aversive state that non-valued effort would otherwise effectuate (i.e., when it is registered as a cost in the cost-benefit ratio).

Although the present exercise studies did not assess subjective effort directly, there is evidence that indirectly supports this proposition: Across these studies, a small subsample of participants consistently reported stable or even higher levels of recovery after compared to before the physical exercise (Part II, Studies 2-4 and Part III, Study 2). Note that this phenomenon persisted even when we introduced the measure of mental recovery as a means to differentiate physical exertion from mental activation (Part II, Study 4 and Part III, Study 2). One potential yet highly speculative reason for this finding might be that these people experienced their exerting effort as inherently valuable, which in turn might have shielded them from feeling exhausted, because spending effort was registered as a benefit in their respective cost-benefit ratios.

Interest and Boredom

Contrary to effort, the present exercise studies included a measure of interest and boredom (assessed as two opposite ends on a bipolar dimension), which has emerged as an important covariate: People with a steeper increase in interest (steeper decrease in boredom) during the recovery period also reported a steeper increase in mental recovery and positive mood, a more pronounced acceleration of subjective time perception, and a less steep increase in perceived opportunity costs (Part II, Study 4 and Part III, Study 2). The same pattern held for the exhaustion period in Part III, Study 2, with the addition that interest was negatively (boredom positively) related to physical exhaustion. In light of these findings, how might interest and boredom relate to the proposed account in Part I?

First, research has shown that interest can lead to greater exertion of effort and greater persistence in demanding tasks than mere task pleasantness (Thoman et al., 2011). This finding is corroborated by Milyavskaya, Galla, Inzlicht, and Duckworth (2018), who found that compared to non-interested people, interested people are more likely to exert greater effort on a mentally demanding task, all the while reporting lower feelings of exhaustion.

Thus, it seems as though interest is distinguishable from mere enjoyment (see also Silvia, 2008), and might shield a person from feelings of exhaustion and motivate her to persist longer on demanding tasks.

This proposal is in line with research on autonomous motivation (i.e., interest inherent in a task; Deci & Ryan, 2000): People who are intrinsically motivated to engage in a demanding self-regulation task show less decrements in task performance, reduced feelings of exhaustion, and increased feelings of so-called "vitality" (Ryan & Deci, 2008). Furthermore, inherent or autotelic interest in a task itself is also a core assumption of flow theory (Csikszentmihalyi, 1975; Nakamura & Csikszentmihalyi, 2014). The experience of flow (also known as the "optimal experience") can arise if one is "engaging challenges at a level appropriate to one's capacities" (Nakamura & Csikszentmihalyi, 2014, p. 90), and if the desired goal is specific and feedback about one's progress toward it is immediate. Flow, then, is characterized by a focus on the process of goal pursuit (see also Freund & Hennecke, 2015), the sense that one is in control of the situation, a loss of reflective self-consciousness, an accelerated subjective time perception, and the experience of the activity as intrinsically rewarding (Nakamura & Csikszentmihalyi, 2014).

Second, in an experience sampling study, Milyavskaya, Inzlicht, Hope, and Koestner (2015) found that when people were currently engaging in *want-to* goals (i.e., goals that reflect a person's genuine interest and values and are personally important and meaningful), they reported fewer and weaker conflicting desires along with a stronger resistance toward these desires as compared to when they were currently engaging in *have-to* goals (i.e., goals that are mainly pursued due to external incentives or introjects such as shame; Inzlicht et al., 2014). Similarly, Sheldon and Elliot (1998) found that people who reported more autonomous motivation for their personal goals were more likely to achieve them, because they invested more effort compared to people who reported more “controlled” motivation for their goals.

Taken together, I maintain that the desirable characteristics pertaining to interest and, by extension, to the experience of flow, are registered as a *benefit* in the cost-benefit ratio of an activity, and hence lead to positive mood (Thoman et al., 2011), an accelerated subjective time perception (Nakamura & Csikszentmihalyi, 2014), and an enhanced value of the focal activity along with a decreased value of competing goals (Milyavskaya et al., 2015), thus keeping opportunity costs at a low level. As a consequence, interest and flow are likely to facilitate recovery and shield against exhaustion.

The flip side of interest is boredom, “the aversive state of wanting, but being unable, to engage in a satisfying activity” (Eastwood, Frischen, Fenske, & Smilek, 2012, p. 483). Recent research has shown that bored people who work on a very easy task report higher subsequent feelings of exhaustion than non-bored people who work on a difficult task (Milyavskaya et al., 2019). It seems that boredom arising from understimulation and meaninglessness (van Tilburg & Igou, 2012) contributes to the subjective sense of exhaustion (but see Westgate & Wilson, 2018, for an overview of the different kinds of boredom). In addition to boredom being aversive and exhausting, studies have found that the experience is accompanied by an extended subjective time perception (Danckert & Allman, 2005) and motivates people to seek out more valuable activities (Westgate & Wilson, 2018). Taken together, then, experiencing boredom during an ongoing activity is likely registered as a cost in its cost-benefit ratio, contributing to an increase in negative mood, extended subjective time perception, and an increase in perceived opportunity costs, thereby facilitating feelings of exhaustion (for a conceptual distinction between boredom and exhaustion, see Part I).

The Curious Case of Goal Focus and Effort

When people pursue a goal, they can at any given point in time focus more on the process or outcome of goal pursuit. Process focus denotes the degree to which people attend to the "how" of pursuing a goal; outcome focus denotes the degree to which people attend to the "why" of pursuing a goal (Freund & Hennecke, 2015; Freund et al., 2012; Kaftan & Freund, 2018). In short, the *process* of goal pursuit entails a focus on the more proximal and concrete means (e.g., going for a run), takes place in specific contexts (e.g., on the treadmill at home or in the forest outside), and guides goal-related actions (e.g., by focusing one's attention on controlled breathing). In comparison, the *outcome* of goal pursuit entails a focus on the more distal and abstract ends (e.g., enhancing one's physical attractiveness), provides a clear standard of comparison between the actual and desired future state (e.g., how does one look like now compared to how one wishes to look like), and gives direction and meaning (Freund & Hennecke, 2015). Here, I propose two opposing possibilities on how goal focus might affect the salience and perceived value of effort during goal pursuit.

On the one hand, when people focus more on the process of goal pursuit, the effort one invests into goal-related activities (e.g., running) should become more salient. At first glance, this might result in a decrease in the hedonic valence of the activity, because effort is usually experienced as aversive (Kurzban, 2016; but see Inzlicht et al., 2018). However, people often make use of the *effort heuristic*, according to which the more effort they perceive themselves investing into the pursuit of a goal, the more valuable they perceive the associated outcome to be (Kruger et al., 2004). In turn, the more valuable an outcome, the more persistently people strive to attain it (Eccles & Wigfield, 2002). Thus, one might argue that people who adopt a process focus during the pursuit of an activity might ascribe more value to the invested effort and perceive the phenomenology of effort as more pleasant, which – ceteris paribus – might shield them longer from feelings of exhaustion and enable prolonged activity engagement.

Indeed, people with the goal to start exercising regularly reported more positive affect, a higher exercise frequency and regularity, and an overall higher goal attainability over a period of four months when they were focusing more on the process as compared to the outcome of goal pursuit (Freund, Hennecke, & Riediger, 2010). Similarly, in a 6-week longitudinal study on weight loss in overweight women, Freund and Hennecke (2012) found that focusing more on the process of dieting (e.g., dietary behaviors) was positively and focusing more on the outcome of dieting (e.g., weight loss) was negatively related to actual weight loss. Finally, in an 8-week longitudinal study on the role of goal focus for adherence to a high-intensity interval training, Kaftan and Freund (2019) found that people who focused more on the process of exercising were more likely to achieve their self-selected workout goals and were overall more satisfied with their workout compared to people who focused more on the outcome of exercising.

On the other hand, adopting an outcome focus is more likely to direct attention toward the higher-order goal, hence making it more accessible (Freund & Hennecke, 2015). In turn, “an accessible goal evokes a need to assess the usefulness or instrumentality of a particular means [activity] in fulfilling that goal” (Labroo & Kim, 2009, p. 133). According to the *instrumentality heuristic*, people perceive the accompanying sense of effort as indicating that the activity is instrumental for achieving the desired goal, hence increasing its value and hedonic valence (see also the “affective transfer” effect; Fishbach, Shah, & Kruglanski, 2004), and thus shielding the person from feelings of exhaustion. In fact, in their exercise adherence study, Kaftan and Freund (2019) found that focusing on the outcome of exercising was positively related to the perceived importance and pleasantness of the workout and contributed to positive mood, over and above focusing on the process of exercising.

Boundary Conditions of the Proposed Account

The proposed motivational account of exhaustion and recovery is not universally valid and comes with a number of non-negligible boundary conditions. For instance, by taking an affect-as-information approach (Clore et al., 2001; Clore & Huntsinger, 2007; Huntsinger et al., 2014), we have argued that people use their positive and negative mood as information about the goodness or badness of the current activity, and judge their extent of exhaustion and recovery based on their momentary affective experience. However, this approach might only be valid in situations in which people perceive the ongoing activity as the source of their mood. As Huntsinger et al. (2014, p. 602) aptly state, "the information conveyed by affect, and its consequences for judgment and cognitive processing, depend on how the experience of affect is *attributed* [emphasis added]." What happens if a person running a marathon attributes her mood to another source (e.g., to accessible pleasant or distressing thoughts, the temperature, or the weather; Schwarz & Clore, 1983) instead of the ongoing activity? In such a situation, it becomes less likely that the person perceives negative changes in her mood as an indication that running is starting to feel exhausting (or, conversely, that watching TV is no longer contributing to her recovery). As a consequence, the person might persist longer in an ongoing activity that has started to net more costs than benefits.

Another boundary condition pertains to the nature of the subjective *stop rule* people employ to determine when they should disengage from an activity. For instance, in a classic study conducted by Martin et al. (1993), participants in either positive or negative moods were given a pile of cards containing behavioral statements about a fictitious person and were instructed to form an impression of the person based on these statements. Half of the participants were told to read the statements until they felt that they had acquired enough information for forming their impression (i.e., "enough information" condition), whereas the other half were told to continue reading the statements until they no longer enjoyed the task (i.e., "enjoy" condition). Consistent with the idea that positive mood serves as a "go" signal and negative mood as a "stop" signal, happy persons in the "enjoy" condition took their positive mood as information that they were still enjoying the task, and thus the implication was that they should continue reading the statements. In contrast, sad persons took their negative mood as information that they were not enjoying the task, and consequently they stopped sooner. Importantly, these effects *reversed* in the "enough information" condition. That is, happy persons stopped reading the statements *sooner* than did sad persons, because their positive mood implicated that their stop rule had been fulfilled. This finding implies that the influence of mood on cognition and behavior is not fixed but malleable (Huntsinger et al., 2014); that is, positive and negative mood might act as a "go" and "stop" signal for any *cognitively accessible mental content* in a given situation (e.g., a specific stop rule). Thus, contrary to the fixed predictions of the proposed account, persons who rely on a "enough recovery/exhaustion" as compared to a "enjoy" stop rule to determine their momentary state (i.e., "Have I recovered enough/Am I exhausted yet?" as compared to "Am I still enjoying this activity?") might disengage faster from the ongoing activity if they are in a good mood, as opposed to a bad mood, and might therefore underestimate their current extent of recovery and exhaustion (Martin, 2001).

On a related note, in their cybernetic control theory, Carver and Scheier (2004) argue that experiencing positive (negative) mood during the pursuit of a goal is an indication that the rate of progress toward goal attainment is faster (slower) than expected. In this view, the mood experienced during an ongoing activity is indicative of *goal progress*, rather than of the favorableness of the activity's cost-benefit ratio. As a consequence, according to this theory, people in a good mood are more likely to reduce effort (i.e., "coast") and people in a bad mood are more likely to increase effort, in an attempt to minimize the discrepancy between the perceived and the expected or desired rate of progress toward the goal. Thus, to the extent that this theory is applicable on the activity level, if a person's focus of attention lies on the rate of progress during a recovery or exhausting activity, they might perceive negative changes in their mood as an indication that they need to "catch up" rather than disengage, and therefore increase their expended effort in order to achieve the desired goal, hence making goal disengagement due to a decline in mood less likely. Louro, Pieters, and Zeelenberg (2007) could show that *goal proximity* is an important moderator of this relationship: When the goal is still distal, positive mood leads to higher expenditure of effort and negative mood to a reduction of effort. Only when the goal looms close are these relationships reversed and start behaving according to the theory of Carver and Scheier (2004).

Finally, the proposed account mainly operates under the assumption that the recovery activity is a *unifinal* means (i.e., mainly serves to accomplish a single goal – recovery), and that people disengage from it once they have sufficiently recovered. However, in the hectic pace of daily life we are often faced with the necessity of pursuing more than one goal at a time (e.g., Riediger, 2007). Hence, means that are *multifinal* (i.e., simultaneously serve to advance multiple goals; Kruglanski et al., 2002) are generally perceived as more valuable compared to unifinal means (Kruglanski et al., 2013). Arguably, most daily recovery activities such as watching TV or reading a book are multifinal means in the sense that they serve other goals in addition to recovery (e.g., maintaining social relationships, personal growth, environmental mastery; Ryff, 1995). As such, to the extent that these additional goals are salient while a person recovers (but see the "goal shielding" effect; Shah, Friedman, & Kruglanski, 2002), once the goal of recovery is reached and consequently deactivated (Förster, Liberman, & Higgins, 2005), people might still perceive a strong motivational link between the ongoing activity and the additional goals, therefore sustaining the value of the activity past the point of recovery, and consequently they keep engaged in it.

Methodological Considerations and Future Directions

The present thesis is not without limitations. First and foremost, it relied on single-item self-report measures of the variables of interest, because the nature of the study designs necessitated a trade-off between methodological precision and empirical feasibility. Nevertheless, single-item measures are by definition less reliable than multi-item measures. Furthermore, self-report measures can be affected by various cognitive and affective processes, such as social desirability, acquiescent responding, and extreme responding (for a comprehensive overview of different response styles, see Paulhus & Vazire, 2007), possibly resulting in common method bias. However, despite these concerns, the single-item measures used in the present studies showed good within-person reliability (R_{Cn}s between .81 and .87; Cranford et al., 2006), indicating that these items were sensitive in detecting between-person differences in within-person change over time. Furthermore, the multilevel models were able to capture intraindividual variability in these items remarkably well, as is evident from the modest amount of within-person random effects (i.e., error variance), as well as the consistently large amount of explained variance in subjective recovery and exhaustion by the model-fitted fixed and between-person random effects of interest (e.g., between 74% and 85% in Parts II and III). In addition, as outlined in the Introduction, the present thesis was mainly concerned with taking a *phenomenological* approach toward exhaustion and recovery. Given that persons are “the best-qualified witnesses” (Paulhus & Vazire, 2007, p. 227) of their own internal states (cf. Nisbett & Wilson, 1977), the use of self-report measures for these study designs is warranted.

To complement this self-report approach, future laboratory research should consider an additional *behavioral* measure of goal disengagement, such as having participants directly indicate when they feel sufficiently exhausted or recovered and want to do something else. For instance, Hofmann et al. (2019, Study 5) developed a promising opt-out paradigm that gives participants the opportunity to abandon a focal task at different exit points in favor of another task. Such an approach would enable a more direct test of the effect of an opportunity cost manipulation on goal disengagement, as it arguably provides a more precise insight into the exact point in time when a person begins to perceive more net costs than benefits of an ongoing activity. In addition, this would also allow for a more comprehensive test of the reversible relationships between mood, perceived opportunity costs, subjective time perception and recovery and exhaustion proposed in Part I.

Second, the present studies assessed the central constructs of interest – state exhaustion and recovery – on a bipolar continuum. One problem with this approach is the difficulty of interpreting the scale midpoint and the extremes: Do values around the midpoint indicate that persons are neither exhausted nor recovered? Do values close to one extremum (e.g., recovery) indicate an absence of the state that is tied to the other extremum (e.g., exhaustion)? Consequently, these measures do not allow for the possibility of joint occurrences of recovery and exhaustion (in a single functional domain) in situ. However, the fact that the separate trait measures of exhaustion and recovery developed in Part V consistently showed medium-to-large to large interrelations in our studies (*r*s between -.44 and -.73) is an indication that their state measure counterparts are characterized by similarly high levels of interdependence. Furthermore, in the exhaustion and recovery literature, there is general agreement that it is not the within-domain (e.g. physical exhaustion and recovery), but rather the cross-domain (e.g., physical and mental exhaustion and recovery) relationship between exhaustion and recovery that might be qualitatively distinct (Inzlicht & Marcora, 2016) – a notion that we controlled for by measuring physical and mental exhaustion and recovery separately in Part II, Study 4 and Part III, Study 2.

Third, the intensive micro-longitudinal self-report design employed in the exercise studies raises issues related to *reactance* (Brehm, 1966) and *reactivity* (French & Sutton, 2010). That is, it might have become frustrating for people to answer the same questions pertaining to their momentary experiences every two minutes, and the mere process of answering these questions might have had a non-negligible impact on their subsequent experience and behavior. However, post-hoc control checks revealed that the repeated measures were generally perceived as not too distracting for the recovery process (*M*s between 2.08 and 2.65, *SD*s between 1.33 and 1.56 on a scale ranging from 0 [*not at all distracting*] to 5 [*very distracting*] in Part II, Studies 2-4), indicating that the chosen timing interval was adequate. Furthermore, these repeated measures might have progressively directed people's attention away from the recovery activity toward their bodily sensations (i.e., interoception; Craig, 2002) and made these internal processes more artificially salient than they would be naturally perceived in a similar situation in everyday life, thereby limiting the studies' external validity. In fact, goal progress monitoring – while generally beneficial for attaining one's goals (Harkin et al., 2016) – might hinder the attainment of a goal that is an *internal state*[3] (Shapira, Gundar-Goshen, Liberman, & Dar, 2013; see also the "affect labeling" effect; Lieberman, Inagaki, Tabibnia, & Crockett, 2011). On a related note, an increased interoceptive focus might be a further explanation as to why subjective time perception gradually extended during the recovery period (Pollatos, Laubrock, & Wittmann, 2014).

To address these issues, it might seem like a straightforward solution for future laboratory work to incorporate non-invasive and continuous physiological measures in addition to the repeated self-reports and potential behavioral measures. However, as outlined in the Introduction, it is unclear in most cases how to interpret this large swath of physiological data and, more specifically, how it relates to the accompanying subjective experience (Marcora, 2009). Thus, absent more in-depth theoretical and empirical work, as of

[3] I thank Dr. Oliver Kaftan for bringing this particular matter to my attention.

yet it is not possible to provide a satisfactory and conclusive solution to this methodological problem in the context of exhaustion and recovery (and for emotion research more broadly; Barrett et al., 2007). In spite of this, there have been some promising recent advances, one of which merits particular mention in this regard: Wrzus et al. (2014) developed a novel assessment of physiological recovery as the time until a person's heart rate reaches her individual confidence interval of the baseline heart rate. Importantly, the authors convincingly demonstrated that this measure converged substantially with affective self-reports across different age groups and over time.

Finally, future research should strongly consider assessing exhaustion and recovery in everyday life using experience sampling methodology (Larson & Csikszentmihalyi, 2014; Bolger & Laurenceau, 2013). Doing so allows for the necessary disentanglement of the influence of *contextual variables* (e.g., time of day, life domain, social dynamics, location) and *activity characteristics* (e.g., expectancy, value, demand, valence) on *subjective experiences* in situ (e.g., exhaustion, recovery, mood, opportunity costs). For instance, future work could more closely examine differences in the experiential aspects of goal pursuit in the context of work and leisure. In a classic experience sampling study, Csikszentmihalyi and LeFevre (1989) encountered the seemingly paradoxical situation that although people generally reported more positive affect and found themselves in a state of flow more often when at work as compared to when at leisure, they also wished to be doing something else more often when at work than when at leisure. It might be interesting in this regard to examine divergences in the specific *content* of these opportunity costs in the work and leisure domain. For instance, one could differentiate between opportunity costs that refer to want-to and ought-to alternative goals (Riediger & Freund, 2008; see also Inzlicht et al., 2014) and examine their differential effect on exhaustion and recovery.

Furthermore, taking an experience sampling approach enables the investigation of the effect of *day-level variables* (e.g., sleep quality, day of the week) on these subjective experiences. For instance, in their daily diary study, Sonnentag et al. (2008) found that people felt more exhausted in the morning when they reported a poorer-than-usual sleep quality the night before. It would be interesting to examine how sleep quality affects the dynamics of exhaustion and recovery over a whole day, and whether these negatively affected persons can benefit from specific self-regulation or mood enhancement strategies to "propel" them back toward a more manageable level of exhaustion and recovery (Balkin & Wesensten, 2011).

Practical Implications

In the words of the late Robert Thayer (1997, p. 22): "If it [energy] could be bottled, packaged, or taught, someone could make a lot of money." The present thesis does not provide a convenient tell-all answer on how to "bottle up" or "package" energy. It does, however, teach us about the important role of mood and – to a lesser degree – of perceived opportunity costs in shaping the phenomenology of exhaustion and recovery. Building on these focal empirical insights, here I focus on the (1) *subjective experiences* people can seek out in situations where they wish to engage in recovery, and (2) *self-regulatory strategies* people can employ in situations where they have to persist on aversive tasks despite feeling exhausted and the urge to stop.

First, how to efficiently enhance one's mood and recover? Is it a viable strategy to engage in random leisure activities (e.g., watching TV) and wait for recovery to happen? Research strongly suggests that it is less the *amount of time* spent in pleasurable activities but rather the *diversity of experiences* one encounters along the way that enable recovery (Kuykendall et al., 2015) – a fact that is also reflected in the present work in form of the substantial between-person variability in the subjective recovery time courses (Part II, Studies 2-4, Part III, Study 2). Accordingly, what works for one person might not work for another (or might not work for the same person at another time or in a different context). Indeed, contrary to the well-researched strategies people can employ to regulate their shorter-term emotions (for a meta-analysis, see Webb, Miles, & Sheeran, 2012), less is known about the ways people can regulate their longer-lasting moods. Nevertheless, there have been some promising attempts at systematizing such mood regulation strategies across persons, time, and contexts. For instance, building on previous work in this area (e.g., Larsen, 2000; Parkinson & Totterdell, 1999; Thayer et al., 1994), Sonnentag and Fritz (2007) theoretically derived and empirically validated the beneficial effect of *psychological detachment*, *relaxation*, *mastery*, and *control* for recovery. Termed "recovery experiences," these factors have been consistently shown to aid in one's mood regulation following stressful work demands (for a recent overview, see Sonnentag et al., 2017). In light of the inherent difficulty involved in classifying specific everyday life activities as either facilitating or inhibiting recovery due to the large amount of between-person variability (Knecht & Freund, 2015), the work of Sonnentag and Fritz (2007) provides an elegant solution to this problem by elucidating the relevant subjective experiences an activity should foster in order for a person to recover.

Note that in our own work, we found mixed results concerning the effectiveness of these recovery experiences: Only relaxation and control, but not psychological detachment and mastery, were non-negligible predictors of daily recovery (Part IV). Furthermore, we found that positive mood substantially contributed to recovery *over and above* these experiences. Thus, these factors are most certainly not the "be-all and end-all" recovery enablers. There are likely more experiences that can help shape a person's mood and recovery, such as interest (Part II, Study 4 and Part III, Study 2) or a sense of meaning and affiliation (Newman et al., 2014).

Second, how to persist on an aversive task that has seemingly become too exhausting to continue, as indicated by an increase in negative mood and in motivational conflict (e.g., perceiving opportunity costs in the form of pervasive thoughts about attractive alternatives that vie for one's attention)? The straightforward answer is to simply disengage from the task and to seek out these more pleasant endeavors instead. In many instances, however, it is neither easily possible nor particularly prudent to do so. Consider, for instance, being stuck in an arduous meeting that cannot be postponed and necessitates generating concrete solutions to a tough problem. The default behavior in such a situation might consist of seeking out respite in the form of "mental leisure" at regular intervals (Inzlicht et al., 2014). However, mentally distracting oneself from an ongoing aversive activity (e.g., through mind wandering; Killingsworth & Gilbert, 2010) is an ill-suited strategy to regulate one's persistence on it (Hennecke, Czikmantori, & Brandstätter, 2019). Self-regulatory strategies that seemingly work well for promoting one's persistence on such tasks, according to Hennecke et al. (2019), consist of *focusing on the positive consequences* of the activity (cf. Fishbach & Choi, 2012; Freund & Hennecke, 2012), *goal progress monitoring* (for a meta-analysis, see Harkin et al., 2016), *thinking of the near finish*, and *emotion regulation* (see also Tamir, 2016). One explanation for the effectiveness of these strategies might be that they enhance the salience of discrepancy reductions between the actual and desired state over time (Carver & Scheier, 2004).

Importantly, Hennecke et al. (2019) provide an even more fine-grained analysis as to the kinds of self-regulatory strategies that are particularly beneficial for persistence based on the prevailing subjective *cost* of the exhausting activity. For instance, if a person perceives the aversive activity as mainly *mentally effortful*, two particularly viable strategies consist of *goal setting* and *monitoring*. Importantly, according to goal setting theory (Locke & Latham, 2002, 2006, 2019), goals have to be specific and reasonably difficult to attain (and should not, for instance, be formulated as mere “do-your-best goals”) in order to promote persistence. Thus, in situations where people have to persist on aversive tasks that feel mentally effortful, they could set goals such as “I am going to continue working on this manuscript until I have finished the present chapter and have proof-read it at least once” and remind themselves to regularly monitor their progress toward this goal. In contrast, if *boredom* is mainly contributing to exhaustion, the strategy of *task enrichment* (i.e., adding a pleasant component to the activity) seems particularly appropriate. For instance, when one inevitably gets bored of reading a poorly written manuscript but has to nonetheless see it through, one could add a pleasant layer to this activity by listening to one’s favorite music playlist.

Conclusion: A Tale of Shifting Utilities

We all know it: Feeling “spent” after demanding exercise, “worn out” after a long day at work, or “drained” after an intense emotional argument. The present thesis suggests that these shorter-term feelings of exhaustion are not the result of the depletion of some metabolic energy resource; rather, these aversive states help us to juggle the demands of daily life by alerting us of the waning *utility* of our current strivings: When an activity tires us out, we are hereby given a strong motivational cue that we are better off allocating our precious commodities to other, more promising avenues and not to needlessly waste them in futile endeavors. A key player in this tale of shifting utilities, the present thesis finds, is our *mood* – the way we feel about the current environment. Do we feel good about it? The implication is that the environment is safe and benign, and it therefore helps us to recover. Do we feel bad about it? Something about the environment must be off and this could hurt us or hinder us from pursuing our personal goals; hence, we feel exhausted and should make an effort to change course.

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APPENDIX

Appendix A: Additional Tables

Table A1

Means and Standard Deviations of the Dependent Variables Before and After the High-Intensity-Interval Training, along with the 95% CIs of the Mean Difference and Effect Sizes (Part II, Study 2).

	Before		After			
Variable	*M*	*SD*	*M*	*SD*	95% CI	Cohen's *d*
Recovery	1.07	2.03	-1.51	2.19	[2.11, 3.04]	0.82
Mood	2.10	1.74	2.05	1.88	[-0.31, 0.40]	0.02
Time Perception	0.71	1.89	0.37	2.24	[-0.09, 0.76]	0.11
Opportunity Costs	-2.04	2.12	-1.47	2.50	[-1.01, -0.12]	-0.18
Valence	1.55	1.73	0.82	2.09	[0.32, 1.14]	0.26

Note. $N = 134$.

Table A2

Means and Standard Deviations of the Dependent Variables Before and After Stair Running, along with the 95% CIs of the Mean Difference and Effect Sizes (Part II, Study 3).

	Before		After			
Variable	*M*	*SD*	*M*	*SD*	95% CI	Cohen's *d*
Recovery	1.25	2.33	-2.33	2.27	[3.07, 4.10]	0.73
Mood	2.55	1.66	1.88	2.14	[0.26, 1.07]	0.24
Time Perception	1.00	2.19	0.83	2.36	[-0.35, 0.67]	0.05
Opportunity Costs	-2.38	2.20	-1.60	2.85	[-1.28, -0.27]	-0.20

Note. $N = 129$.

Table A3

Means and Standard Deviations of the Dependent Variables Before and After Stair Running, along with the 95% CIs of the Mean Difference and Effect Sizes (Part II, Study 4).

	Before		After			
Variable	*M*	*SD*	*M*	*SD*	95% CI	Cohen's *d*
Physical Recovery	0.96	1.94	-1.49	2.12	[2.01, 2.89]	0.89
Mood	2.00	1.73	2.07	1.78	[-0.40, 0.25]	-0.03
Time Perception	0.76	2.15	1.18	2.23	[-0.86, 0.02]	-0.14
Opportunity Costs	-2.30	2.19	-1.82	2.58	[-0.89, -0.06]	-0.14
Mental Recovery	1.36	2.20	1.79	1.82	[-0.81, -0.05]	-0.14
Interest	0.61	2.04	1.33	1.93	[-1.04, -0.40]	-0.27

Note. $N = 150$.

Table A4

Bayesian Multivariate Multilevel Growth Curve Model Estimates of the Random Slopes Correlations (Part II, Study 3).

Random Slope	1	2	3
1. Recovery	–		
2. Mood	**.50 [.31, .67]**	–	
3. Time Perception	.11 [-.14, .34]	**.49 [.25, .69]**	–
4. Opportunity Costs	-.14 [-.36, .09]	**-.38 [-.59, -.15]**	**-.44 [-.64, -.20]**

Note. N = 129. Reported are the means of the posterior distributions (95% credible intervals in brackets). Correlations in bold are substantial (their 95% CIs do not include 0).

Table A5

Bayesian Multivariate Multilevel Growth Curve Model Estimates of the Random Slopes Correlations (Part II, Study 4).

Random Slope	1	2	3	4	5
1. Physical Recovery	–				
2. Mood	**.32 [.10, .52]**	–			
3. Time Perception	-.06 [-.30, .17]	**.33 [.06, .56]**	–		
4. Opportunity Costs	.06 [-.17, .28]	-.09 [-.34, .16]	**-.50 [-.69, -.27]**	–	
5. Mental Recovery	**.25 [.03, .46]**	**.48 [.24, .67]**	.11 [-.16, .37]	**-.29 [-.51, -.05]**	–
6. Interest	.04 [-.18, .27]	**.27 [.02, .49]**	**.59 [.36, .78]**	**-.69 [-.83, -.51]**	**.30 [.06, .53]**

Note. N = 150. Reported are the means of the posterior distributions (95% credible intervals in brackets). Correlations in bold are substantial (their 95% CIs do not include 0).

Table A6

Multilevel Growth Curve Models for all Variables During the Exhaustion Period as a Function of Time, Age, and Their Interaction (Part III, Study 2).

	Dependent Variable					
Fixed Effects	Physical Recovery	Mental Recovery	Opportunity Costs	Mood	Time Perception	Interest
Intercept	**1.79**	**1.98**	**-2.04**	**2.96**	**1.56**	**1.51**
	[1.52, 2.06]	**[1.69, 2.27]**	**[-2.42, -1.65]**	**[2.71, 3.20]**	**[1.25, 1.86]**	**[1.19, 1.82]**
Time	**-0.99**	**0.17**	**-0.45**	**-0.13**	**0.58**	**0.61**
	[-1.15, -0.84]	**[0.09, 0.26]**	**[-0.65, -0.25]**	**[-0.17, -0.09]**	**[0.39, 0.76]**	**[0.44, 0.77]**
Time^2	**0.12**	**-0.02**	**0.13**	–	**-0.17**	**-0.18**
	[0.09, 0.15]	**[-0.03, -0.02]**	**[0.09, 0.17]**		**[-0.20, -0.13]**	**[-0.21, -0.14]**
Time^3	**-0.01**	–	**-0.01**	–	**0.01**	**0.01**
	[-0.01, -0.00]		**[-0.01, -0.00]**		**[0.01, 0.01]**	**[0.01, 0.01]**
Age	0.01	**0.02**	-0.01	0.00	**0.02**	**0.02**
	[-0.00, 0.02]	**[0.01, 0.04]**	[-0.03, 0.01]	[-0.01, 0.02]	**[0.00, 0.03]**	**[0.00, 0.03]**
Age x Time	**-0.02**	**-0.01**	**0.03**	-0.00	**-0.01**	**-0.01**
	[-0.03, -0.01]	**[-0.01, -0.03]**	**[0.02, 0.04]**	[-0.00, 0.00]	**[-0.02, -0.00]**	**[-0.02, -0.00]**
Age x Time^2	**0.00**	**0.00**	**-0.01**	–	**0.00**	**0.00**
	[0.00, 0.00]	**[0.00, 0.00]**	**[-0.01, -0.00]**		**[0.00, 0.00]**	**[0.00, 0.00]**
Age x Time^3	**-0.00**	–	**0.00**	–	-0.00	**-0.00**
	[-0.00, -0.00]		**[0.00, 0.00]**		[-0.00, 0.00]	**[-0.00, -0.00]**
Random effects						
Between-person						
Intercept	1.40	1.70	1.98	1.27	1.40	1.65
Time	0.60	0.41	0.63	0.20	0.58	0.49
Time^2	0.05	0.03	0.05	–	0.05	0.03
Time^3	0.00	–	–[a]	–	–[a]	0.00
Within-person						
Residual	0.92	0.87	1.33	1.00	1.25	1.06
AR(1)	.26	.21	.52	.49	.59	.47
Marginal R^2	.23	.03	.11	.04	.10	.11
Conditional R^2	.85	.79	.79	.75	.71	.80

Note. N = 147, 11 measurement occasions, 1,616 observations. Time is coded 0 to 10. Age is mean-centered. The fixed effects are reported as unstandardized regression coefficients (their 95% CIs in brackets). The fixed effects in bold are significant (their 95% CIs do not include 0). The random effects are reported as standard deviations and correlations. Marginal R^2 depicts the proportion of variance explained by the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined (Nakagawa & Schielzeth, 2013; Johnson, 2014).

[a]Due to model convergence issues, we had to omit this random effect parameter.

Appendix

Table A7

Multilevel Growth Curve Models for all Variables During the Recovery Period as a Function of Time, Age, and Their Interaction (Part III, Study 2).

	Dependent Variable					
Fixed Effects	Physical Recovery	Mental Recovery	Opportunity Costs	Mood	Time Perception	Interest
Intercept	**-1.80**	**1.55**	0.00	**1.65**	0.28	0.13
	[-2.15, -1.44]	**[1.19, 1.91]**	[-0.45, 0.46]	**[1.29, 2.00]**	[-0.08, 0.63]	[-0.24, 0.49]
Time	**2.15**	**0.69**	**-2.10**	**0.87**	**0.45**	**1.35**
	[1.96, 2.34]	**[0.49, 0.89]**	**[-2.41, -1.78]**	**[0.70, 1.04]**	**[0.22, 0.67]**	**[1.12, 1.57]**
$Time^2$	**-0.36**	**-0.12**	**0.47**	**-0.19**	**-0.10**	**-0.31**
	[-0.41, -0.32]	**[-0.16, -0.07]**	**[0.40, 0.54]**	**[-0.22, -0.15]**	**[-0.16, -0.05]**	**[-0.37, -0.26]**
$Time^3$	**0.02**	**0.00**	**-0.03**	**0.01**	**0.01**	**0.02**
	[0.02, 0.02]	**[0.00, 0.01]**	**[-0.03, -0.02]**	**[0.00, 0.01]**	**[0.00, 0.01]**	**[0.02, 0.02]**
Age	-0.00	0.00	-0.00	0.00	**0.02**	0.01
	[-0.02, 0.01]	[-0.01, 0.03]	[-0.02, 0.02]	[-0.01, 0.02]	**[0.00, 0.04]**	[-0.01, 0.03]
Age x Time	0.00	-0.00	0.01	**-0.01**	-0.01	**-0.02**
	[-0.01, 0.00]	[-0.02, 0.00]	[-0.01, 0.02]	**[-0.02, -0.00]**	[-0.02, 0.00]	**[-0.03, -0.01]**
Age x $Time^2$	0.00	0.00	-0.00	**0.00**	0.00	**0.00**
	[-0.00, 0.00]	[-0.00, 0.00]	[-0.01, 0.00]	**[0.00, 0.00]**	[-0.00, 0.00]	**[0.00, 0.01]**
Age x $Time^3$	-0.00	-0.00	0.00	-0.00	-0.00	**-0.00**
	[-0.00, 0.00]	[-0.00, 0.00]	[-0.00, 0.00]	[-0.00, 0.00]	[-0.00, 0.00]	**[-0.00, -0.00]**
Random effects						
Between-person						
Intercept	1.96	1.92	2.08	2.05	1.64	1.84
Time	0.71	0.52	1.04	0.77	0.46	0.76
$Time^2$	0.06	0.04	0.10	0.07	0.00	0.07
$Time^3$	0.00	0.00	0.00	0.00	0.00	–[a]
Within-person						
Residual	1.02	1.17	1.88	0.79	1.47	1.33
AR(1)	.41	.15	.56	.33	.50	.52
Marginal R^2	.29	.05	.08	.04	.02	.04
Conditional R^2	.85	.71	.62	.86	.69	.75

Note. N = 147, 10 measurement occasions, 1,470 observations. Time is coded 0 to 9. Age is mean-centered. The fixed effects are reported as unstandardized regression coefficients (their 95% CIs in brackets). The fixed effects in bold are significant (their 95% CIs do not include 0). The random effects are reported as standard deviations and correlations. Marginal R^2 depicts the proportion of variance explained by the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined (Nakagawa & Schielzeth, 2013; Johnson, 2014).

[a]Due to model convergence issues, we had to omit this random effect parameter.

Table A8

Bayesian Multivariate Multilevel Growth Curve Model Estimates of the Random Slopes Correlations During the Exhaustion Period (Part III, Study 2).

Random Slope	1	2	3	4	5
1. Physical Recovery	–				
2. Mood	**.35 [.15, .52]**	–			
3. Time Perception	**.28 [.06, .48]**	**.49 [.32, .65]**	–		
4. Opportunity Costs	**-.43 [-.61, -.23]**	**-.47 [-.63, -.30]**	**-.48 [-.64, -.30]**	–	
5. Mental Recovery	**.44 [.25, .61]**	**.62 [.47, .74]**	**.26 [.05, .44]**	**-.40 [-.56, -.22]**	–
6. Interest	**.28 [.07, .47]**	**.55 [.38, .69]**	**.57 [.39, .71]**	**-.54 [-.68, -.37]**	**.37 [.18, .53]**

Note. $N = 147$. Reported are the means of the posterior distributions (95% credible intervals in brackets). Correlations in bold are substantial (their 95% CIs do not include 0).

Table A9

Bayesian Multivariate Multilevel Growth Curve Model Estimates of the Random Slopes Correlations During the Recovery Period (Part III, Study 2).

Random Slope	1	2	3	4	5
1. Physical Recovery	–				
2. Mood	**.36 [.17, .54]**	–			
3. Time Perception	.20 [-.01, .40]	**.38 [.17, .57]**	–		
4. Opportunity Costs	-.01 [-.23, .21]	**-.26 [-.47, -.03]**	**-.48 [-.67, -.27]**	–	
5. Mental Recovery	**.48 [.28, .65]**	**.72 [.55, .86]**	**.35 [.12, .57]**	-.24 [-.46, .02]	–
6. Interest	.01 [-.20, .22]	**.41 [.20, .59]**	**.47 [.28, .64]**	**-.75 [-.88, -.59]**	**.36 [.12, .57]**

Note. $N = 147$. Reported are the means of the posterior distributions (95% credible intervals in brackets). Correlations in bold are substantial (their 95% CIs do not include 0).

Table A10

Bayesian Multilevel Model Estimates for Daily Recovery and Optimal Recovery Proximity as a Function of Daily Mood, Opportunity Costs, Time Perception, Psychological Detachment, Relaxation, Mastery, and Control (Part IV).

	Daily Recovery								Daily Optimal Recovery Proximity							
	Baseline Model				Covariates Model				Baseline Model				Covariates Model			
			95% CI				95% CI				95% CI				95% CI	
Fixed effects	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper
Intercept	-0.48	0.15	-0.77	-0.19	-2.59	0.40	-3.37	-1.80	-0.05	0.21	-0.45	0.37	-1.93	0.49	-2.91	-0.98
Time	0.05	0.01	0.02	0.07	0.05	0.01	0.03	0.07	0.09	0.01	0.07	0.12	0.09	0.01	0.07	0.12
Mood																
Within	0.35	0.03	0.28	0.41	0.24	0.04	0.17	0.31	0.19	0.03	0.14	0.24	0.16	0.03	0.11	0.21
Between	0.27	0.07	0.12	0.41	0.23	0.08	0.07	0.38	0.10	0.12	-0.12	0.33	0.08	0.11	-0.13	0.29
Opportunity Costs																
Within	-0.21	0.03	-0.26	-0.16	-0.08	0.02	-0.13	-0.03	-0.12	0.02	-0.15	-0.08	-0.09	0.02	-0.12	-0.06
Between	-0.15	0.07	-0.28	-0.02	0.06	0.07	-0.08	0.20	-0.21	0.08	-0.37	-0.06	0.03	0.09	-0.14	0.21
Time Perception																
Within	0.08	0.03	0.02	0.14	0.08	0.03	0.02	0.13	0.04	0.02	0.00	0.07	0.03	0.02	-0.00	0.06
Between	0.22	0.07	0.08	0.35	0.14	0.07	-0.00	0.27	0.16	0.09	-0.01	0.33	0.03	0.08	-0.14	0.20
Detachment																
Within	-	-	-	-	0.01	0.04	-0.08	0.09	-	-	-	-	0.07	0.03	0.01	0.13
Between	-	-	-	-	0.17	0.12	-0.05	0.41	-	-	-	-	0.22	0.14	-0.05	0.49
Relaxation																
Within	-	-	-	-	0.61	0.06	0.49	0.74	-	-	-	-	0.16	0.04	0.08	0.23
Between	-	-	-	-	0.27	0.13	0.00	0.53	-	-	-	-	-0.49	0.18	-0.84	-0.14
Mastery																
Within	-	-	-	-	0.06	0.05	-0.03	0.15	-	-	-	-	0.08	0.03	0.02	0.14
Between	-	-	-	-	-0.07	0.09	-0.25	0.11	-	-	-	-	0.05	0.10	-0.16	0.26
Control																
Within	-	-	-	-	0.12	0.06	0.01	0.24	-	-	-	-	0.09	0.04	0.02	0.17
Between	-	-	-	-	0.43	0.12	0.20	0.65	-	-	-	-	0.89	0.15	0.60	1.19
Recovery																
Within	-	-	-	-	-	-	-	-	0.35	0.02	0.30	0.39	0.30	0.02	0.25	0.34
Between	-	-	-	-	-	-	-	-	0.31	0.10	0.11	0.49	0.55	0.10	0.36	0.75

Table A10 (continued)

	Daily Recovery								Daily Optimal Recovery Proximity							
	Baseline Model				Covariates Model				Baseline Model				Covariates Model			
			95% CI				95% CI				95% CI				95% CI	
Random effects	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper	Est.	*SE*	Lower	Upper
Between-person																
Intercept	0.85	0.08	0.70	1.00	0.77	0.07	0.64	0.92	1.21	0.09	1.04	1.40	1.07	0.08	0.93	1.23
Time	0.10	0.01	0.07	0.12	0.10	0.01	0.07	0.12	0.16	0.01	0.13	0.18	0.15	0.01	0.12	0.17
Mood	0.15	0.06	0.03	0.26	0.19	0.05	0.09	0.28	0.18	0.03	0.13	0.24	0.17	0.03	0.12	0.22
Opp. Costs	0.15	0.04	0.07	0.22	0.07	0.04	0.00	0.15	0.11	0.02	0.06	0.16	0.06	0.03	0.00	0.11
Time Perception	0.23	0.03	0.16	0.29	0.17	0.03	0.10	0.23	0.08	0.03	0.02	0.13	0.10	0.02	0.05	0.14
Detachment	-	-	-	-	0.24	0.05	0.13	0.34	-	-	-	-	0.18	0.04	0.11	0.25
Relaxation	-	-	-	-	0.43	0.06	0.32	0.55	-	-	-	-	0.22	0.04	0.13	0.30
Mastery	-	-	-	-	0.19	0.07	0.03	0.32	-	-	-	-	0.15	0.05	0.05	0.24
Control	-	-	-	-	0.28	0.07	0.14	0.43	-	-	-	-	0.18	0.06	0.05	0.30
Recovery	-	-	-	-	-	-	-	-	0.18	0.02	0.14	0.23	0.17	0.02	0.13	0.22
Within-person																
Residual	1.96	0.03	1.90	2.03	1.75	0.03	1.69	1.82	1.22	0.02	1.18	1.27	1.13	0.02	1.09	1.18
AR(1)	0.08	0.03	0.03	0.14	0.09	0.03	0.03	0.15	0.12	0.03	0.06	0.18	0.08	0.03	0.02	0.14
LOO–IC	10168	77.20			9236	80.00			8190	105.10			7561	96.30		
Marginal R^2		.28				.40				.42				.51		
Conditional R^2		.43				.57				.77				.80		

Note. N = 147 persons, 21 days, 2,332-2,342 observations. Est = Estimate. Depicted are the unstandardized regression coefficients for the fixed effects and the standard deviations and correlations for the random effects. LOO–IC = Approximate leave-one-out cross-validation information criterion based on the posterior likelihood (smaller values indicate better model fit). Marginal R^2 depicts the proportion of variance explained by the fixed effects. Conditional R^2 depicts the proportion of variance explained by the fixed and random effects combined. Time is mean-centered (0 represents day 10 after the final exam). The default priors of the brms R-package (Bürkner, 2017) were used.

Appendix B: General Exhaustion and Recovery Scale

State Version of the Exhaustion and Recovery Scale

Instruction. Below is a list of statements. Please read each statement carefully and indicate the extent to which these statements apply to you right now, in this moment. There are no right or wrong answers. We are interested in how you personally feel right now. Please answer as honestly as you can.

Recovery Subscale

Right now…
1. …I feel energized.
2. …I feel refreshed.
3. …I feel that I'm doing things better than usual.
4. …I could tolerate the pressure very well.
5. …I could stay active for a long time.

Exhaustion Subscale

Right now…
1. …I feel burned out.
2. …I feel like I'm at the end of my rope.
3. …I feel weak.
4. …I find everything getting on top of me.
5. …I'm in a bad mood.
6. …I feel sickened by everything.
7. …I'm indifferent toward everything.
8. …I feel like doing nothing.

Scoring. Item responses are measured on a scale of 0 (*not at all*) to 5 (*very much*). The item presentation order is randomized.

CURRICULUM VITAE

Name	Brian B. Cardini
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Academic Education

01/2016 – present	**Doctoral Candidate, University Research Priority Program "Dynamics of Healthy Aging", University of Zurich** Research topic: Indicators of Exhaustion and Recovery Across the Lifespan Advisor: Prof. Dr. Alexandra M. Freund
03/2016 – present	**LIFE Fellow and Speaker** International Max Planck Research School on the Life Course (LIFE, www.imprs-life.mpg.de)
02/2014 – 01/2016	**Master of Science in Psychology, University of Basel** Area of specialization: Developmental and Personality Psychology
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Professional Positions

08/2015 – 12/2015	Internship at the School Psychological Services, Basel, Switzerland
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